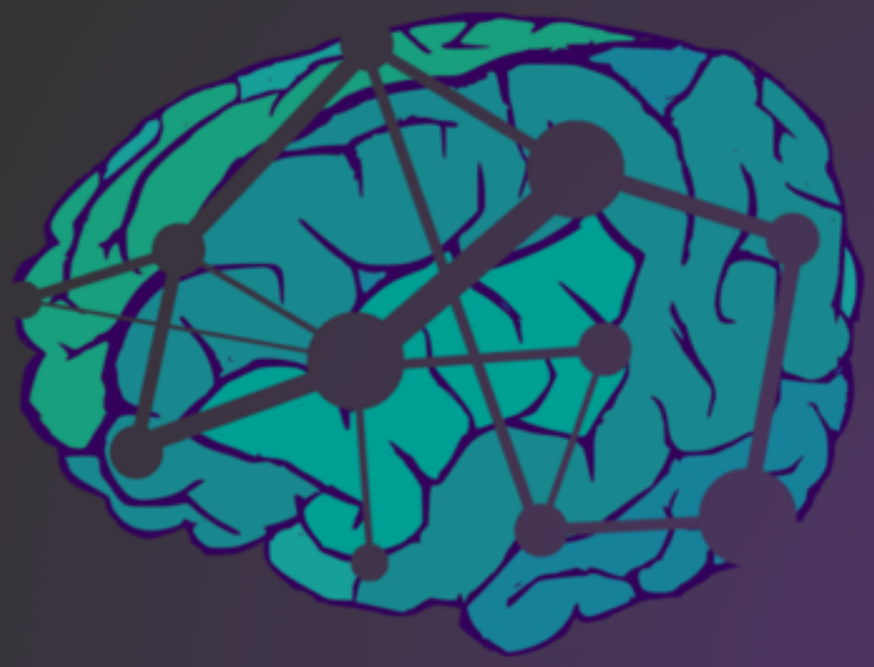
neurodata.io

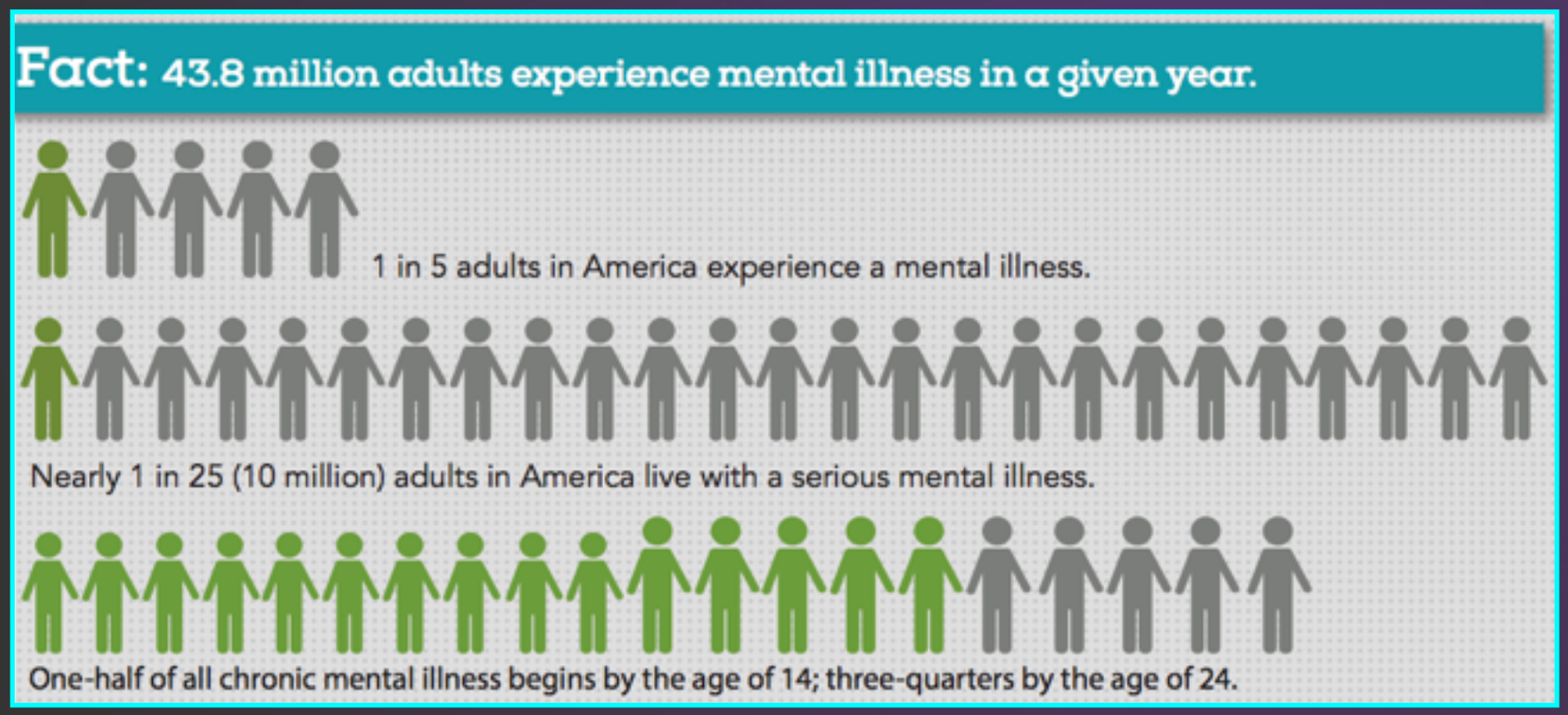


HOCKEY: How to Observe Connectomes for gaining Knowledge and Estimating ‘Y’

Greg Kiar

March 7th, 2016

Significance



NAMI: https://www.nami.org/NAMI/media/NAMI-Media/Infographics/GeneralMHFacts.pdf

Gap

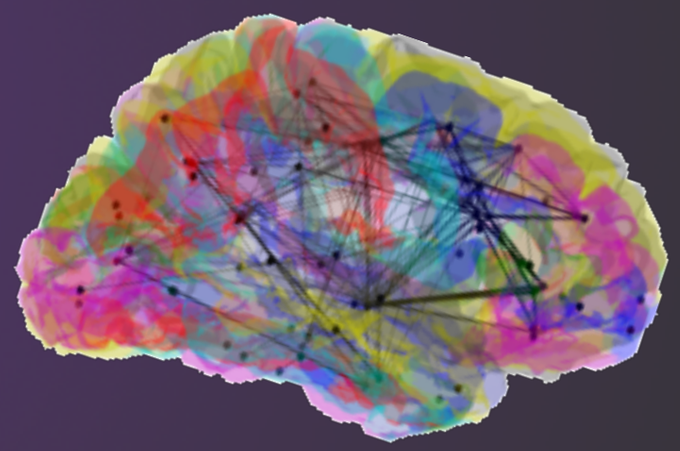
- Currently, no brain imaging biomarkers exist that are clinically useful for any diagnostic category in psychiatry

- Currently, no known open source sex (or other covariate) classifiers based on connectome analysis exist

APA 2012: Consensus Report of the APA Work Group on Neuroimaging Markers of Psychiatric Disorders RESOURCE DOCUMENT

Challenge

- Graph stats are hard:
  - Large number of dimensions (D)
  - Small number of samples (N)
  - Observations are noisy
  - Batch effects across studies



Formal Statement of Problem

$$G_i, Y_i \sim \mathcal{F} = \{F_{G,Y}(\cdot;\theta) : \theta \in \Theta)$$

Graphs and labels observed

$$Y_i = \{0, 1\}$$

Y is our binary label vector

CLASSIFY

$$l = \sum \mathbb{I}(\hat{Y}_i \neq Y_i)$$

We calculate loss based on correct assignment

$$E[l] = \sum \mathbb{I}(\hat{Y}_i \neq Y_i)/N$$

And get expected loss

Model Assumptions

$$G_i, Y_i \overset{i.i.d}{\sim} F \in \mathcal{F}$$

Graphs are i.i.d.

$$F_{GY} = F_{G|Y} F_Y$$

A class conditional difference exists

$$F_{G|Y} \in \mathcal{F}_{G|Y}$$

$$F_Y = Bern(\pi)$$

Formal Statement of Algorithm

Algorithms used:

- Linear Discriminant Analysis (LDA)
- Quadratic Discriminant Analysis (QDA)
- K-Nearest Neighbours (KNN)
- Support Vector Machine (SVM)
- Random Forrest (RF)

QDA:

Quadratic Score Function:

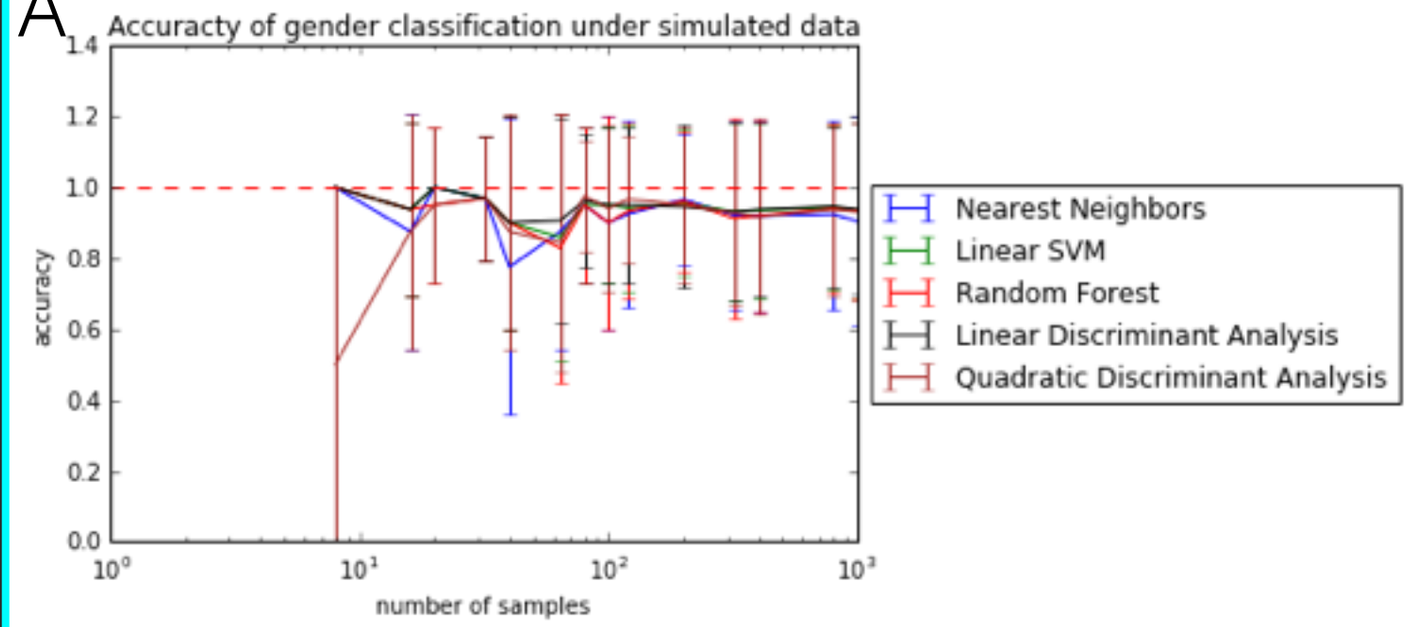
$$s_i^Q(\mathbf{x}) = -\frac{1}{2}\ln|\Sigma_i| - \frac{1}{2}(\mathbf{x}-\mu_i)^T\Sigma_i^{-1}(\mathbf{x}-\mu_1) + \ln p_i$$

Becomes Decision Rule:

$$s_i^Q(\mathbf{x}) = -\frac{1}{2}\ln|S_i| - \frac{1}{2}(\mathbf{x}-\bar{\mathbf{x}})^T S_i^{-1}(\mathbf{x}-\bar{\mathbf{x}}) + \ln p_i$$

Results

A



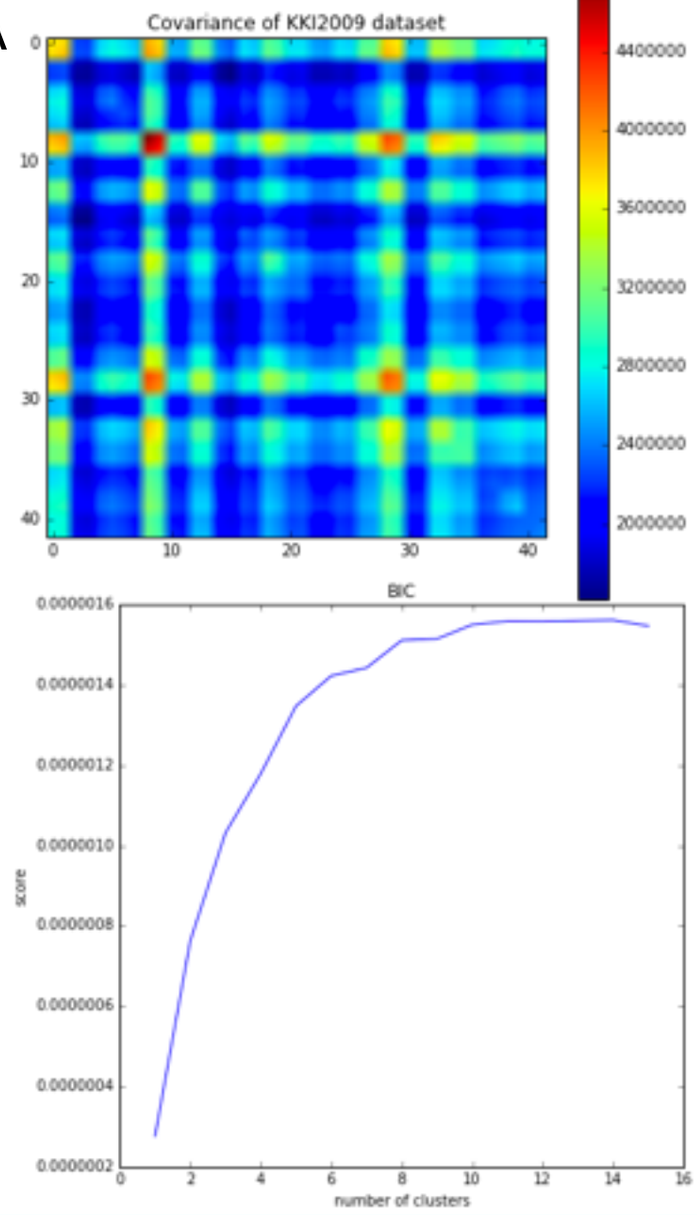
B

Algorithm	Classification Accuracy
Nearest Neighbors	0.48 (+/- 1.00)
Linear SVM	0.55 (+/- 1.00)
Random Forest	0.57 (+/- 0.99)
Linear Discriminant Analysis	0.45 (+/- 1.00)
Quadratic Discriminant Analysis	0.71 (+/- 0.90)

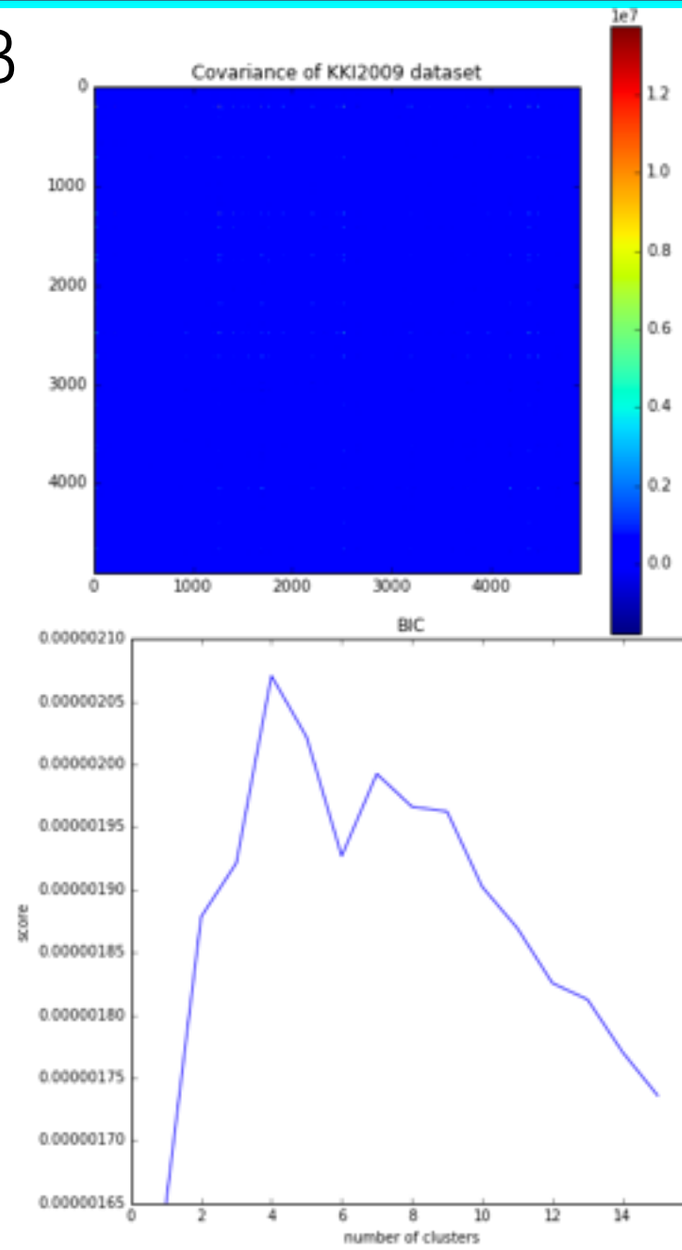
A. The performance of several classifiers on simulated data from our model, showing performance as the number of samples scaled. All algorithms scaled well with N and achieved near perfect accuracy in classification under these conditions. B. Performance of the same classifiers on the given dataset consisting of 42 graphs with 20 and 22 members of class 0 and 1, respectively, and each graph containing 70 nodes. The best classifier used here was the QDA method, which achieved just over 70% classification accuracy.

Model Checking

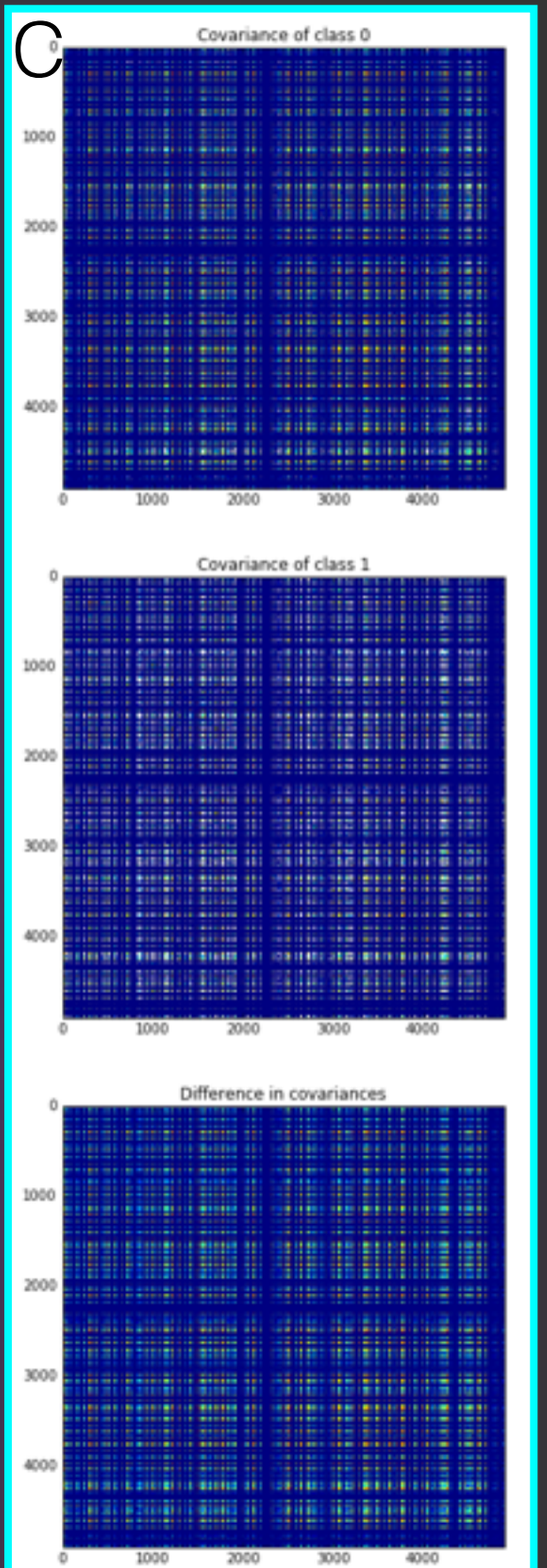
A



B



C



A. We show that the covariance across subjects is non zero and the ideal number of clusters is > 1, indicating both our graph i.i.d. assumptions were false. B. Like A, the same is true for the edge i.i.d. assumption. C. We compared the covariances across classes and found that the difference was very large, suggesting why QDA performed better for classification than LDA, for instance.

Resolution

- The principled approach we took to this problem encourages us to believe the results we obtained
- This is a building block for future studies which can leverage this domain knowledge to build better classifiers for more difficult covariates