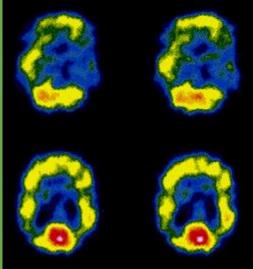
# Insights from SPECT imaging data

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# Significance

Mental health problems develop at a young age.

1 in 5 children have a mental health problem in any given year.8



First experience of mental health problems in those suffering lifetime mental health problems.9

50% by 14 years old

75% by 25 years old

Mental health impacts on life expectancy.

Average life expectancy in England and Wales for people with mental health problems is 60 years behind the national average. 12



FOR EVERYONE



FOR PEOPLE WITH MENTAL HEALTH

**PROBLEMS** 

Mental health is widespread & common.

Every year 1 in 4 adults experience at least one mental disorder. 10





22.8% Mental Health 45.1% Other causes 15.9%

disability in the UK.11

People with mental health problems have worse physical outcomes.

People with mental illness are at increased risk of the top five health killers, including heart disease. stroke, liver and respiratory diseases and some cancers.

#### **PEOPLE WITH SCHIZOPHRENIA ARE:**

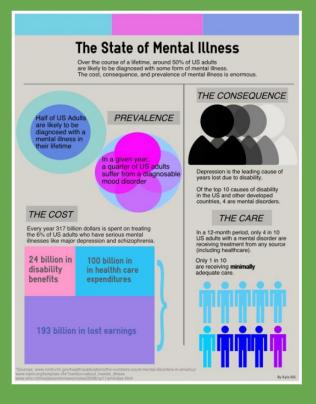
Mental health is a

Mental neal(1) is a significant burden.

Mental ill health is the single largest cause of

more likely to die from cardiovascular disease,

more likely to die from respiratory disease.



### Gap

- Most of the case studies are based on small sets of patient records, such as the SPECT heart dataset
- Currently, no known existing statistical or machine learning tools is widely applied for SPECT imaging analysis
- Most of the case studies are based on a number of clinical observations or limited clinical experience
- Currently, the machine learning studies on SPECT are based on small sets of patient records (SPECT heart dataset)

## Challenge

#### SPECT

- Large number of dimensions (754)
- Noisy observations (lots of NAs etc.)
- Mixed information, needs cleaning and segregation
- Data nature is fat and short post cleaning, 2790 samples with 754 dimensions

# Formal statement of the problem

Patient info and Labels observed:

Y is binary label vector:

We estimate loss based on the number of correct assignments.

Loss functions differ for different classification models.

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

$$Y_i = 0, 1$$

$$\begin{array}{ll} \mathbf{LG} & L = -log P(y|g(X)) = -(y \cdot log(g(X)) + (1-y) \cdot log(1-g(X)) \\ \mathbf{KNN} & L = \sum_{i=1}^{n} D(X_i|y_i = 1, X|y = 1) + \sum_{i=1}^{n} D(X_i|y_i = 0, X|y = 0) \\ \mathbf{SVM} & L = (max\{0, 1 - y \cdot g(x)\})^2 \\ \mathbf{RF} & L = \sum_{i=1}^{n} (g(X_i) - y_i)^2 \\ \mathbf{QDA} & L = max\{0, 1 - y \cdot g(x)\} \end{array}$$

 $X_i, Y_i \stackrel{i.i.d.}{\sim} F \in \mathcal{F}$ 

 $X_{ij}{\sim}F_j\in\mathcal{F}$ 

#### Model Assumptions

We assume that the patients were sampled i.i.d.

We also additionally assume that the features are not identically distributed.

# Formal Statement of Algorithm

- PCA and Sparse PCA
  - o 754 ---> 27
- Post this we trained with a series of classifiers and and tested their accuracies with LOOCV.
  - Logistic Regression
  - o KNN
  - Linear SVM
  - Random Forest
  - QDA

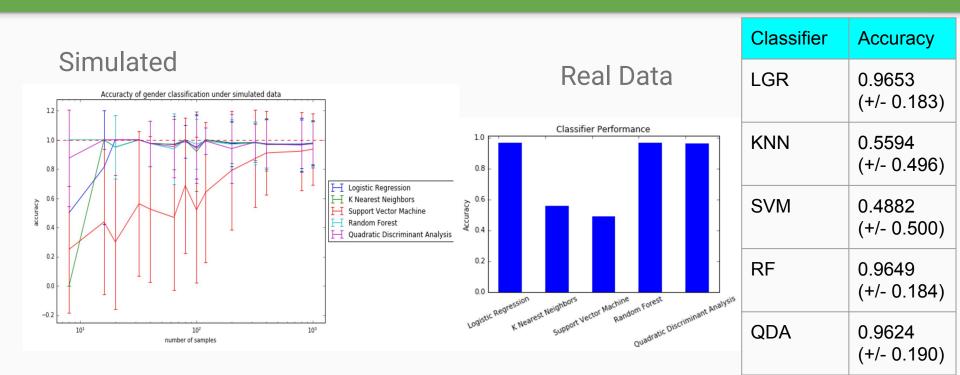
#### The Logistic Function

$$\sigma(t) = \frac{1}{1 + e^{-t}}$$

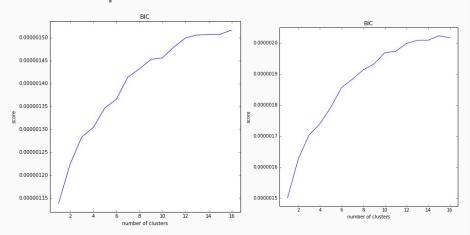
#### **Becomes Decision Rule**

$$F(x) = \frac{1}{1 + e^{-(\beta_0 + \sum_{i=1}^n \beta_i x_i)}}$$

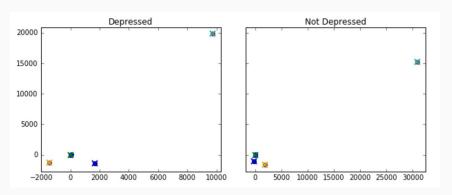
#### Results



#### Sample Clusters



#### **Feature Clusters**



#### Model Checking

We assumed that our samples were i.i.d.

To verify independence we converted the reduced feature set of depressed individuals into a square matrix and then used the matrix rank to determine if the patients are linearly independent. Less than 5% of our samples were not independent.

To verify identicality we used GMM to cluster the samples and K-Means to cluster the features. Neither the samples nor the features are identically distributed.

#### Resolution

- We used a systematic principled approach and we have sufficient samples, therefore we trust our results
- Look into the feature engineering steps
- Look into other relations in our data that we haven't discovered yet

## Thanks!

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