Introduction

Brain structure varies between people in an organized fashion. Inter-individual differences in different parts of brain can covary which is called structural covariance. It has been claimed at times that structural covariance can arise from some sort of physical connectivity of white matter or functional connectivity of neurons.

We used physical connectivity a.k.a thickness to form networks which are used to study structural covariance with respect to age. The aim of the project was to investigate whether the brain networks generated using cortical thickness data are better in predicting the age of the subject compared to only the data itself.

Methods

We used IXI – Information eXtraction from Images (EPSRC GR/S21533/02) public dataset, which is structural MRI data collected from 581 subjects with age ranging from 20-86 years old. We used a smaller subset of the dataset with 327 subjects (188 males and 139 females) and age from ranging from 20-83 years.The dataset was obtained using the following scanners with parameters:

1. Philips Medical Systems Intera 3T (TR = 9.6 ms, TE = 4.6 ms, flip angle = 8°, slice thickness = 1.2 mm, volume size = 256 × 256 × 150, voxel dimensions = 0.94 × 0.94 × 1.2 mm3)
2. Philips Medical Systems Gyroscan Intera 1.5T (TR = 9.8 ms, TE = 4.6 ms, flip angle = 8°, slice thickness = 1.2 mm, volume size = 256 × 256 × 150, voxel dimensions = 0.94 × 0.94 × 1.2 mm3).

The structural MRI data in nifti format was preprocessed using FreeSurfer standard pipeline. For quality control, a 'Quality' parameter was introduced in the dataset where '0' denoted the best quality and '2' denoted the worst quality data.

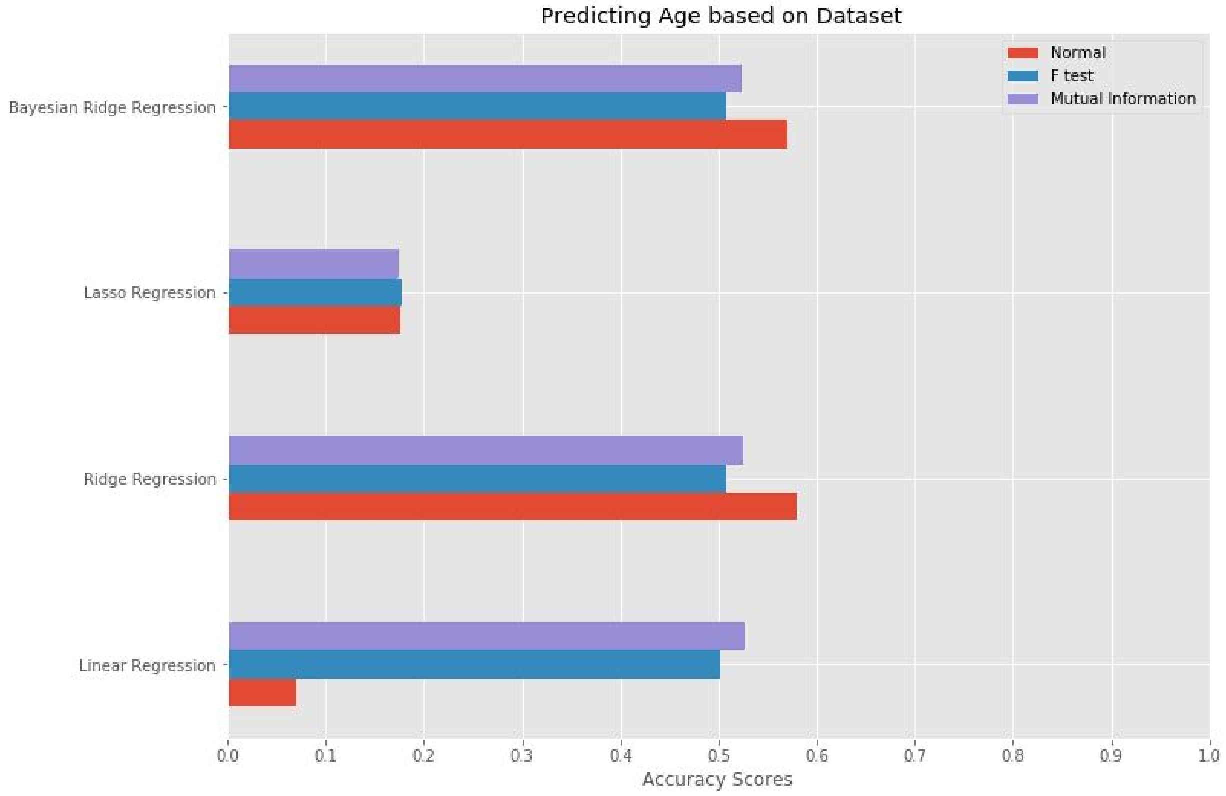
The project was carried out in several steps given as follows:

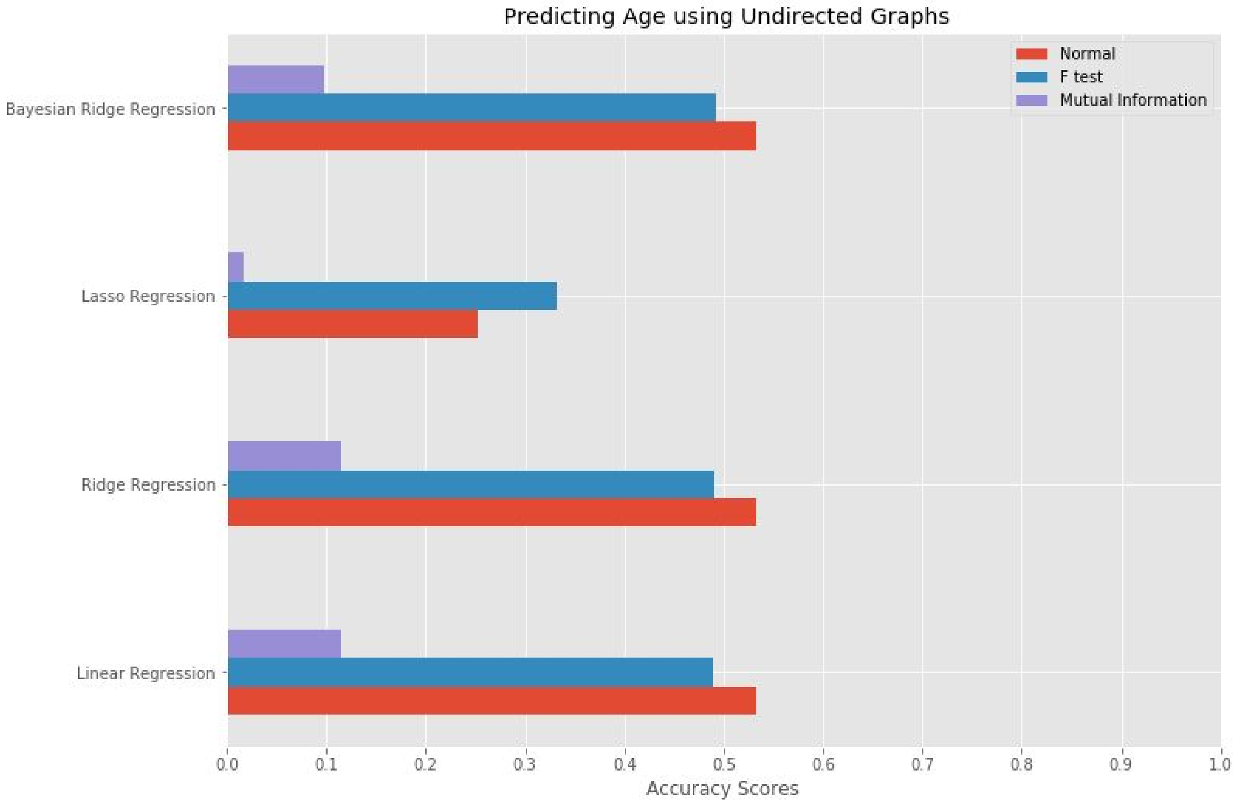
1. First of all, we just performed regression on the dataset to predict the age. Four types of regression were carried out namely - linear regression, ridge regression, lasso regression and bayesian ridge regression. Linear regression uses ordinary least squares but suffers when there is a dependency between two or more variables. Ridge regression improves on linear regression by imposing penalty on size of coefficients but again a feature can't be assigned zero weight even if it doesn't affect the target variable. Lasso regression overcomes the zero weight problem and also imposes penalty for regularisation. Bayesian ridge regression uses probabilistic model based on Bayes theorem for regression.
2. As the results were not satisfactory, we tried to improve the model using feature selection. As the dataset has 148 thickness features, we used only best 10 features for regression based on two different statistical measures - mutual information and f-test statistics. F-test can only capture linear dependency whereas mutual information can capture any kind of dependency between variables.
3. Next, we formed network using cortical thickness data [2]. A node was a thickness features and when the absolute difference between two nodes was less than 0.20 mm they were said to be 'connected' otherwise 'disconnected'. We used two types of graph for prediction - directed and

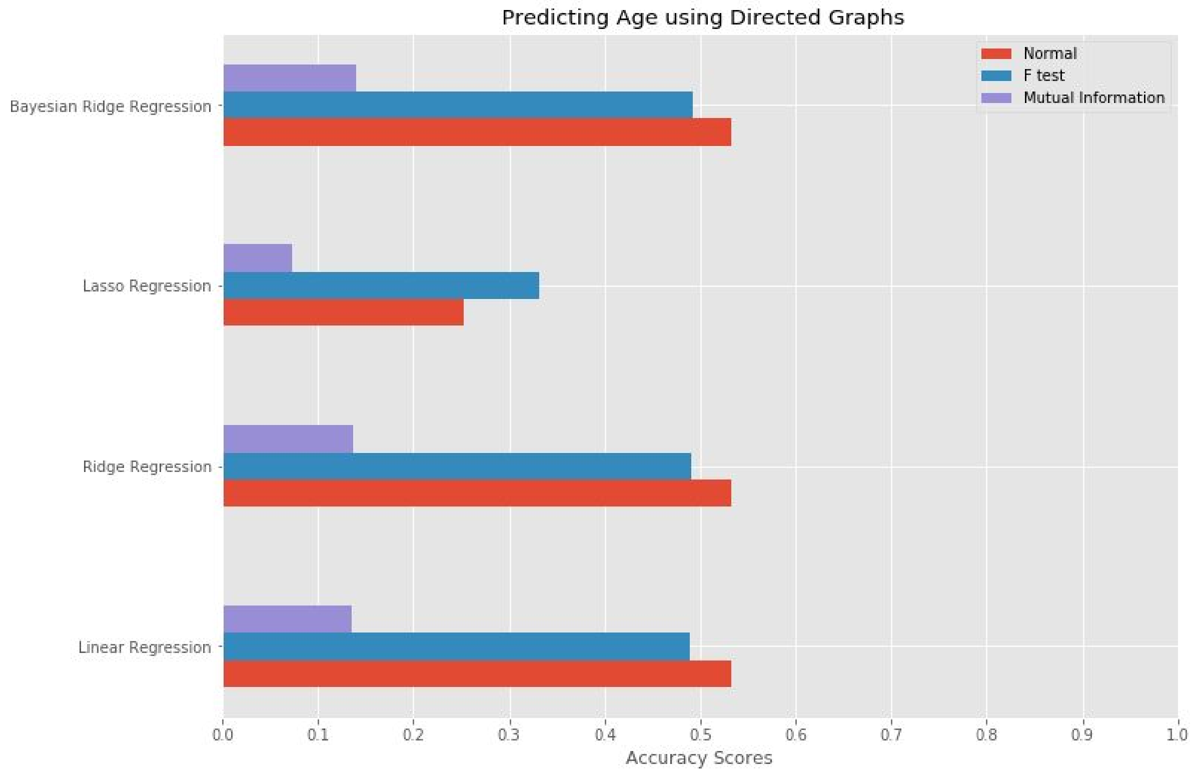
undirected. In undirected graph, connected nodes had a weight of 1 if the edge existed otherwise 0. In directed graph, the absolute difference between two nodes was taken as weight if the edge existed. Later on, we also used feature selection to select the most important edges for prediction.

We used python, numpy, pandas, matplotlib and sklearn for the project. The code for the project is in the form of IPython notebooks and data.csv in the github repository for the course. Link to Repository

Results







Discussion

We couldn't find anything useful in networks generated from individuals. Individual level structural similarity might not hold value but group level structural co-variance might prove useful in analysing how connectivity changes over time in different brain regions and affects our behaviour i.e. old people vs young people.

There were many limitations of the project. First of all, brain network is a geographical network whereas the network used by us was very simple. For the very same reason, the visualization of network didn't make any sense. Secondly, we didn't try to check thickness values other than 0.20 mm or did grid search for hyperparameters to improve the result. Thirdly, we were predicting exact age upto decimal places which could have been improved by taking bins of ages like 20-30, 30-40. Lastly, more data is always welcome.

There are many interesting things that can be learned from this report which are given as follows:

1. The very first interesting thing was that we can make networks from brain thickness data.
2. The report is useful to understand that machine learning techniques can prove useful only when there is more data. Using only the best quality data severely deteriorated our performance.
3. Use regression diagnostics to further improve the result of your predictor. It is also important to perform feature selection and hyperparameter optimization using grid search.

Further extension of this project would be to make more complex geographical network with the help of an expert and use it to study structural covariance.

References

1. Alexander-Bloch A, Giedd JN, Bullmore E. Imaging structural co-variance between human brain regions. *Nature reviews Neuroscience*. 2013;14(5):322-336. doi:10.1038/nrn3465.
2. Raamana, P. R., Wen, W., Kochan, N. A., Brodaty, H., Sachdev, P. S., Wang, L., & Beg, M. F. (2014). Novel ThickNet features for the discrimination of amnestic MCI subtypes. *NeuroImage: Clinical*, *6*, 284-295.