Classifying Child Maltreatment by Brain Imaging Data

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Abstract

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Childhood maltreatment is a condition that leads to the development of behavioral issues and affect brain structure and functionality. Recent neuroimaging studies provide connection between deficits in brain volume, gray and white matter of several cortical regions, such as dorsolateral and ventromedial prefrontal cortex and also hippocampus and amygdala [1].

Machine learning has become the major technique in brain imaging and also computational neuroscience, since they are very seminal for training great amount of neural data of increasing measurement precision and acquiring signals from very noisy data. Machine learning techniques provide the tools to characterize brain states and distinguish them from non-informative brain signals [2].

In this thesis, I use machine learning to classify childhood maltreatment using MRI scans of adolescents and children. The main goal of this thesis project is to find methods to classify childhood maltreatment and find predictive brain regions that contribute to it. I also look at other features such as age and gender, to see how predictable they are based on the brain imaging data.

ACKNOWLEDGMENTS

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Chapter 1
INTRODUCTION: CLINICAL PSYCHOLOGY

In this thesis, I study the effects and contributions of child maltreatment to the brain development in children and adolescents. In this chapter, I start by explaining the underlying motivation for this project, and define related concepts in clinical psychology. I then explain the applications of brain imaging data in child maltreatment. Finally, I present related work on this subject in clinical psychology community.

In chapter 2, I introduce machine learning and related methods. Specifically, I focus on supervised machine learning and classification methods. I discuss concepts such as visualization and feature selection. Finally, I present related work in this field. In chapter 3, the dataset that I experimented on, will be explained in detail. In chapters 4 and 5, I present the results of applying classification and feature selection methods to brain imaging data to predict child maltreatment. Finally, in chapter 6, I give a summary of this thesis and directions for future work.

1.1 Motivation

In 2012, nearly $700,000$ children were determined to be victims of maltreatment in United States, but most importantly is the consequences of the these maltreatment which children and adolescents go through which affects their developing brains which in turn alters their ability to learn, maintain relationships and live a healthy life [3].

The Stress and Development Lab at University of Washington headed by Dr. Katie McLaughlin examines how experiences of stress and adversity impact children's development [4]. "Stressful life events are a universal experience for children, adults, and families" [4]. Projects on early childhood experience and brain development are among ongoing studies in this lab. This thesis project was introduced and conceived by Dr. Katie McLaughlin.

1.1.1 Classifying Child Maltreatment

The main purpose of this thesis is building predictive models to classify child maltreatment using brain imaging data. Being able to predict child maltreatment using brain imaging data can be used to identify children with abusive caretakers, and subsequently finding ways to help maltreated children find activities to potentially repair the changes their brain due to maltreatment.

Although the main purpose of this project is to predict child trauma from brain imaging data, I also use the same methods and techniques to identify predictive clinical features such as age and sex.

1.2 Clinical Psychology

Clinical psychology is a specialty that explores mental care for a single person or a group of people, such as families, communities or companies [5]. Clinical psychology explores mostly in surface of mental psychiatry and therefore a comprehensive knowledge of different areas within psychology is necessary.

1.2.1 Child Clinical Psychology

Clinical child psychology is a subset of clinical psychology that is focused development of infants, children and adolescents within the given social context [6].

1.2.2 Child Maltreatment

Any behavior or action towards a child (or adolescent) that can potentially cause physical or emotional harm is called child maltreatment. There are four basic types of child maltreatment: Neglect, emotional abuse, physical abuse and sexual abuse [7].

Child maltreatment is a major health issue and affects any individual that has been subject to it in terms of psychiatric problems, later in adult life. There are only limited studies to help us understand the relationship between exposure to child maltreatment and issues in development [8].

1.3 Neuroimaging

Magnetic resonance imaging (MRI) uses strong magnetic fields to create images of biological organisms [9]. Neuroimaging is the study of the brain with devices that use MRI as their basic tool such as magnetic resonance scanners. Neuroimaging is the biggest source of quantitative data on brain structure and function [10].

1.3.1 sMRI and fMRI Data

Magnetic resonance imaging (MRI) is often divided into structural MRI (sMRI) and functional MRI (fMRI). Structural MRI is the study of structure of brain, based on gray and white matter concentration within brain [11]. In fact, most of our results are from the structural MRI dataset.

Functional magnetic resonance imaging (fMRI) measures the blood oxygen changes that occur within the brain [9, 12]. fMRI's main use is in determining the important functions different and sometimes very small (subcortical) regions in brain handle. Without fMRI, many important function handling regions in the brain would not be known so far.

1.3.2 FreeSurfer

FreeSurfer is "a suite of tools for the analysis of neuroimaging data that provides an array of algorithms to quantify the functional, connectional and structural properties of the human brain" [13].

Subcortical regions exist below the cortical surface (outside of the brain) and so are measured differently than the cortical regions (regions on the outside of the brain). Automatic image segmentation is used to find sub-cortical structures. In our project, structural MRI scans are processed using FreeSurfer version 5.3 [14]. There are various publications on the usage and applications of FreeSurfer [15, 16, 17].

1.3.3 Structural Brain Regions

As mentioned in Subsection 1.3.2, Brain images are divided into cortical and subcortical regions. Cortical regions are in other words, the outer layer of brain and subcortical regions are very small regions within the interior side of the brain, such as Amygdala. Softwares such as FreeSurfer, maintain a list of cortical regions and also subcortical regions with specific boundaries and can in turn, convert sMRI data to a size list of brain regions. In Figure 1.1, Figure 1.2, and Figure 1.3 you can see FreeSurfer's list of cortical regions in a visual form [13].

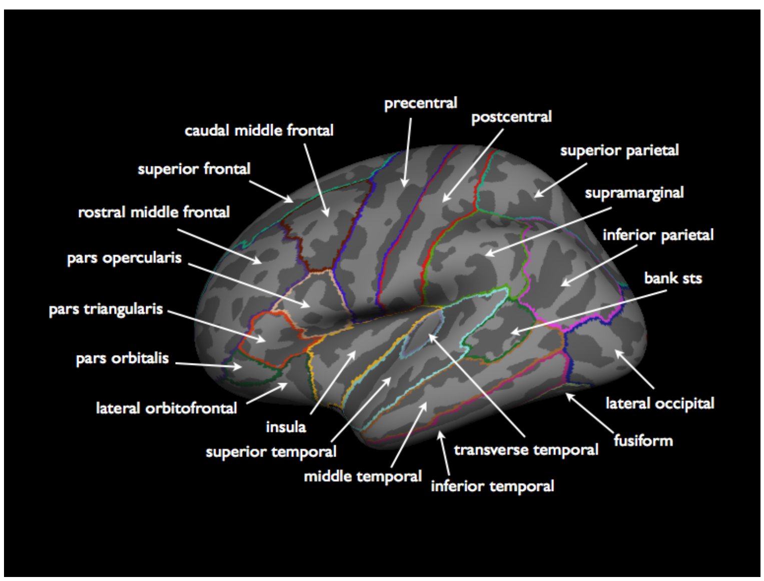

Figure 1.1: Lateral View of Brain Divided to Cortical Regions using Freesurfer

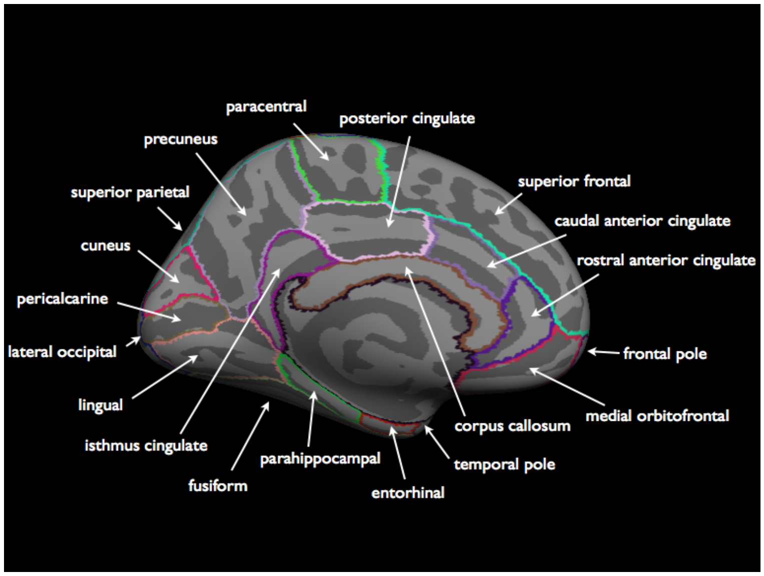

Figure 1.2: Medial View of Brain Divided to Cortical Regions using Freesurfer

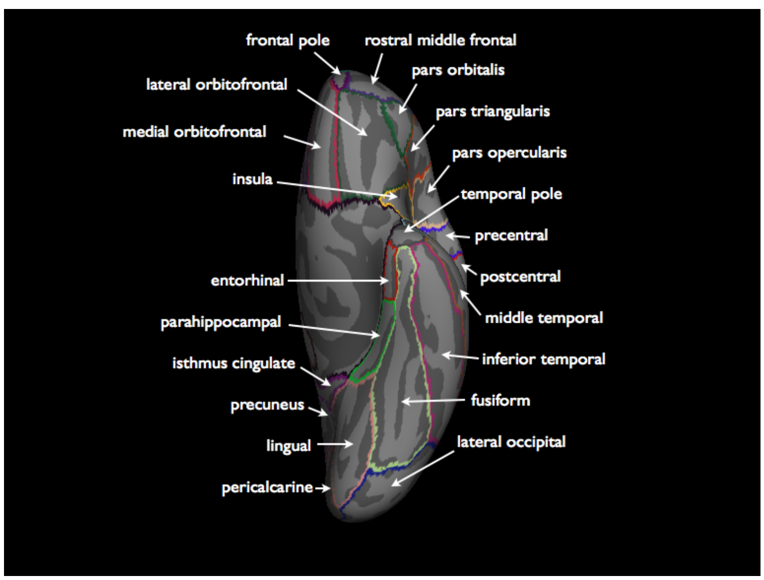

Figure 1.3: Ventral View of Brain Divided to Cortical Regions using Freesurfer

1.4 Related Works

MRI scans have been used a lot recently to explore brains and to show how they work. There are several books explaining how MRI scans are taken and how I can use them to our advantage [9, 12]. Since, there has been numerous studies on pediatric brain development using MRI scans. These studies normally follow a group of children into their adolescence and early adulthood and measure development of different area within the brain [18, 19, 20, 21, 22, 23, 24].

Childhood maltreatment has been shown to significantly elevate the risk of psychiatric disorder. Previous neuroimaging studies of children exposed to maltreatment have reported atypical neural structure in several regions, including the prefrontal cortex and temporal lobes. These studies have exclusively investigated volumetric differences rather than focusing on genetically and developmentally distinct indices of brain structure [8].

There are various structural brain changes associated with childhood maltreatment. Some instances are mentioned here:

- Global Volume or Gray Matter Abnormalities: Abuse or maltreatment in early life has been shown to correlate with structural brain differences. Recent studies have found that brain volume correlated positively with age of onset of trauma and negatively with duration of abuse, suggesting a direct link between abuse and brain structure [25, 26].

- Orbitofrontal Cortex: The orbitofrontal cortex (OFC) is a prefrontal cortex region in the frontal lobes in the brain which is involved in the cognitive processing of decision-making. Mclaughlin *et al.* [27] showed that children reared in institutions exhibited widespread reductions in cortical thickness across prefrontal, parietal, and temporal regions relative to community control subjects and cortical thickness in lateral orbitofrontal cortex, as well as some other regions mediated the association of institutionalization with inattention and impulsivity. There are many studies also showing association of early stress and alterations in the OFC (orbitofrontal cortex) [28, 29, 30, 8].

- Parahippocampal Gyrus: The parahippocampal gyrus is a gray matter cortical region of the brain that surrounds the hippocampus and is part of the limbic system. McLaughlin *et al.* [31] provided results depicting that hippocampal volumes are reduced among children with maltreatment exposure. Lim *et al.* [30] also showed that relative to comparison subjects, individuals exposed to childhood maltreatment exhibited significantly smaller gray matter volumes in parahippocampal gyrus.

- Superior Temporal Gyrus: The superior temporal gyrus is one of three gyri in the temporal lobe of the human brain, which is located laterally to the head, situated somewhat above the external ear. The association between superior temporal gyrus volume and childhood maltreatment has been studied and mentioned in Lim *et al.*'s paper [30]. Other studies also show that superior temporal gyrus volumes are relatively larger in maltreated subjects compared with control subjects [32, 33].

- Middle Temporal Gyrus: Middle temporal gyrus is a gyrus in the brain on the Temporal lobe. It is located between the superior temporal gyrus and inferior temporal gyrus. Results from different papers suggest that maltreated children, compared to non-maltreated peers have reduced gray matter in the middle temporal gyrus [29, 30, 8].

- Inferior Temporal Gyrus: The inferior temporal gyrus is placed below the middle temporal gyrus, and is connected behind with the inferior occipital gyrus. Bremner *et al.*'s research [34] show that during retrieval of emotionally valenced word pairs, PTSD patients with child trauma showed greater decreases in blood flow in an extensive area, which also included inferior temporal gyrus.

- Inferior Frontal Gyrus: The inferior frontal gyrus is a gyrus of the frontal lobe. A study of response inhibition reported increased activation i nsubjects with early life stress compared to controls in the inferior frontal cortex [35].

- Amygdala: The amygdala plays a key role in emotional processing, assessment of threatening information, behavioral regulation, fear conditioning, and memory for emotional events. As these processes are of extreme importance in threatening situations it may be expected that differences in amygdala structure would be associated with exposure to childhood maltreatment [36]. McLaughlin *et al.* [37, 31] found that maltreated adolescents exhibited heightented response in multiple nodes in the salience ntework including amygdala and putamen, to negative relative to neutral stimuli.

There are various and sometimes mixed results regarding association between child maltreatment and different parts of the brain. I refer the reader to Hart and Rubia's review paper [1] for more information.

Chapter 2
INTRODUCTION: MACHINE LEARNING

In this chapter, I will introduce machine learning and methods used in this thesis. I will define machine learning, and explain concepts of classification which is a sub-domain in machine learning. I will also discuss data visualization tools and feature selection in machine learning approaches.

2.1 Machine Learning

Machine learning is the science of helping computers to execute without being explicitly programmed. In the past few years, machine learning has given us many gifts such as self-driving cars, speech recognition, fast web search, and also better understanding of our genome. Many scientists believe that machine learning is a necessary ingredient in coming up with a human-level artificial intelligence [38, 39].

2.1.1 Classification

In machine learning and statistics, classification is the problem of identifying to which of a set of categories (sub-populations) a new observation belongs, on the basis of a training set of data containing observations (or instances) whose category membership is known.

In the last few years there has been growing interest in the use of machine learning classifiers for analyzing fMRI data. A growing number of studies has shown that machine learning classifiers can be used to extract exciting new information from neuroimaging data [40]. Along with the growth in interest and breadth of application, the methods underlying the use of classifiers with fMRI have continuously evolved and ramified. Given the novelty of the approach, there have been few attempts to organize and interrelate available methods in a single place.

2.2 Visualization

Data Visualization is an essential step in data science to explore and understand the given data [41]. The importance is to the point that if I are not able to see a signal in the data for the different values of the class I are trying to predict, normally I stop and look for approaches to remove or minimize the noise within the input data before going forward. Other option would be to change the feature I are trying to predict.

2.2.1 Heatmap

A heatmap is a graphical representation of data where the individual values contained in a matrix are represented as colors. A simple heatmap provides an immediate visual summary of information. More elaborate heatmaps allow the viewer to understand complex data sets.

There can be many ways to display heatmaps, but they all share one thing in common; They use color to communicate relationships between data values that would be would be much harder to understand if presented numerically in a spreadsheet. Many heatmaps such as one in Figure 4.1 are available throughout this thesis.

2.2.2 Principal Component Analysis (PCA)

Principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components [42]. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to the preceding components. The resulting vectors are an uncorrelated orthogonal basis set. PCA is sensitive to the relative scaling of the original variables.

2.3 Classification Methods

In the terminology of machine learning, classification is considered an instance of supervised learning, i.e. learning where a training set of correctly identified observations is available. The corresponding unsupervised procedure is known as clustering, and involves grouping data into categories based on some measure of inherent similarity or distance.

An algorithm or method that implements classification, especially in a concrete implementation, is known as a classification method or classifier. The term "classifier" sometimes also refers to the mathematical function, implemented by a classification algorithm, that maps input data to a category [43].

Here are some of the classifications methods used in this thesis:

2.3.1 LASSO

In statistics and machine learning, lasso (least absolute shrinkage and selection operator) (also Lasso or LASSO) is a regression analysis method that performs both variable selection and regularization in order to enhance the prediction accuracy and interpretability of the statistical model it produces [44]. It minimizes the usual sum of squared errors, with a bound on the sum of the absolute values of the coefficients. It has connections to soft-thresholding of wavelet coefficients, forward stagewise regression, and boosting methods.

2.3.2 Random Forest

Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks, that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees [45]. Random decision forests correct for decision trees' habit of overfitting to their training set.

2.3.3 Other Methods

Other than the two methods mentioned above, I have tried various methods but had little luck comparing to Lasso and Random Forest. I introduce them here briefly:

- Random Uniform Forest [46]: Ensemble model for classification, regression and unsupervised learning, based on a forest of un-pruned and randomized binary decision trees. Unlike Random Forests, each tree is grown by sampling, with replacement, a set of variables before splitting each node.

- GLM [47]: The generalized linear model (GLM) is a flexible generalization of ordinary linear regression that allows for response variables that have error distribution models other than a normal distribution. The GLM generalizes linear regression by allowing the linear model to be related to the response variable via a link function and by allowing the magnitude of the variance of each measurement to be a function of its predicted value.

- SVM [48]: In machine learning, support vector machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each marked for belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier.

- rpart [49]: Recursive Partitioning and Regression Trees (RPART) is a fundamental tool in data mining. It helps us explore the stucture of a set of data, while developing easy to visualize decision rules for predicting a categorical (classification tree) or continuous (regression tree) outcome.

- BMA [50]: A comprehensive approach to addressing model uncertainty is Bayesian model averaging (BMA), which allows us to assess the robustness of results to alternative specifications by calculating posterior distributions over coefficients and models.

- Ensemble Models: Ensemble modeling is the process of running two or more related but different analytical models and then synthesizing the results into a single score or spread in order to improve the accuracy of predictive analytics and data mining applications.

2.4 Feature Selection

Variable and feature selection have become the focus of much research in areas of application for which datasets with tens or hundreds of thousands of variables are available. These areas include text processing of internet documents, gene expression array analysis, and combinatorial chemistry. The objective of variable selection is three-fold: improving the prediction performance of the predictors, providing faster and more cost-effective predictors, and providing a better understanding of the underlying process that generated the data.

The central premise when using a feature selection technique is that the data contains many features that are either redundant or irrelevant, and can thus be removed without incurring much loss of information.

2.5 Related Works

With rise of fMRI (functional MRI) and sMRI (structural MRI) scans, image-based predictors also started to get developed. Greenstein *et al.* used Random Forest to estimate the probability of being classified as a schizophrenia patient based on MRI measures [51]. Konukoglu *et al.* did an empirical study on two image-based prediction models called neighborhood approximation forests (NAF) and the relevance voxel machine (RVoxM) [52]. Neighbourhood approximation forests, a variant of random decision forests, is a supervised discriminative learning method that uses tree-based approximate nearest neighbour search. Relevance voxel machine, a variant of relevance vector machine (RVM) , is a sparse learning algorithm. Apart from these studies, there are many papers that introduce machine learning techniques for brain imaging [2, 40]. In these introductory papers, several known machine learning methods such as linear models (GLM), KNN (k nearest neighbours), SVM (support vector machine) and some others such as GNB (Gaussian Naive Bayes) and LDA (Fisher's Linear Discriminant Analysis). Overall, linear models are suggested as the best method for MRI data analysis. There are various visualization, validation and feature selection techniques suited for MRI data also mentioned in these tutorial review papers.

Chapter 3
DATA

In this chapter, I will describe the dataset I used for this thesis in detail. Our main dataset is structural MRI (sMRI) data. I also have a relatively small functional MRI (fMRI) dataset which is used in to explore the relationship between its features.

3.1 sMRI Data

A sample of 136 children and adolescents aged 6-19 years participated across two studies [37, 31]. Participants were recruited from a study of adolescents and children with and without child maltreatment exposure. Recruitment efforts were targeted at recruiting a cohort with variations in exposure to maltreatment. A subset of 119 participants (62 with trauma exposure and 57 age-matched and gender-matched controls) completed an MRI study during a separate study visit. All procedures were approved by the Institutional Review Board (IRB) at the University of Washington.

Child abuse was assessed using the Childhood Trauma Questionnaire (CTQ), a self-report measure, and the Childhood Experiences of Care and Abuse (CECA), an interview administered by trained research assistants [53, 54]. The CTQ assesses frequency of physical, sexual, and emotional abuse during childhood and has excellent psychometric properties including internal consistency, test–retest reliability, and convergent and discriminant validity with interviews and clinician reports of maltreatment. The CECA assesses multiple aspects of care giving experiences, including physical and sexual abuse. Interrater reliability for maltreatment reports is excellent, and validation studies find high agreement between siblings on reports of maltreatment. Participants who reported physical or sexual abuse during the CECA interview or who had a score on the physical or sexual abuse subscales of the CTQ above a validated threshold were classified as maltreated. A maltreatment severity score was computed by summing items from the CTQ physical and sexual abuse subscales, given that our sample was recruited based on exposure to these specific forms of abuse.

3.1.1 Samples

As mentioned above, I have 119 samples of children and adolescents. 62 of these samples are maltreated and the other 57 belong to the control group. This dataset consists of two studies provided to me by the Stress and Development Lab at University of Washington: The first study (denoted by $Study1$) consists of 60 samples and is described in detail in [31]; the second study (denoted by $Study2$) consists of 59 samples is reported in [37].

3.1.2 Features

Our dataset consists of a total of 516 features such as age, sex, maltreatment status, abuse scales from the questionnaires, imaging parameters, volume, area and thickness of all cortical regions and volume of all subcortical regions derived using the Freesurfer software:

- Age: The age of samples ranges from 8 to 20. However, the age range between studies is very different. See Figures 3.1 and 3.2.

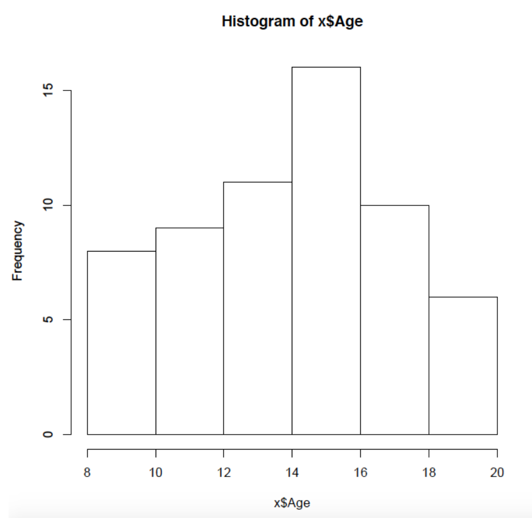

Figure 3.1: Age Histogram of Study1

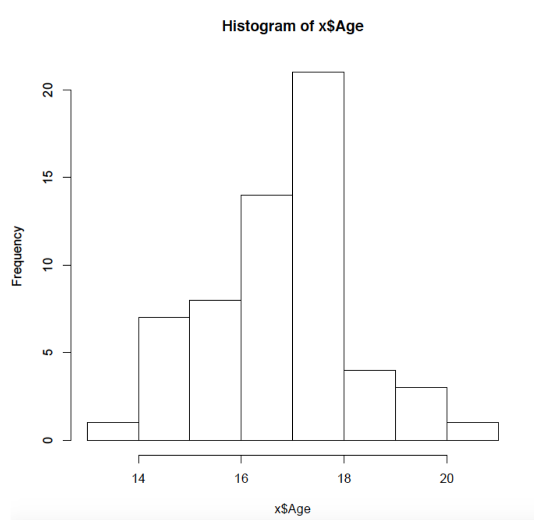

Figure 3.2: Age Histogram of Study2

- Sex: Our dataset consists of 66 females and 53 males.

- Maltreatment Status: This is the feature (or response) I are trying to predict. I have

62 ones and 57 zeros.

- Abuse degrees: I have three features that on a scale of 5 to 25 show degree of emotional, physical and sexual abuse. The histograms of these abuse types are shown in Figures 3.3, 3.4 and 3.5.

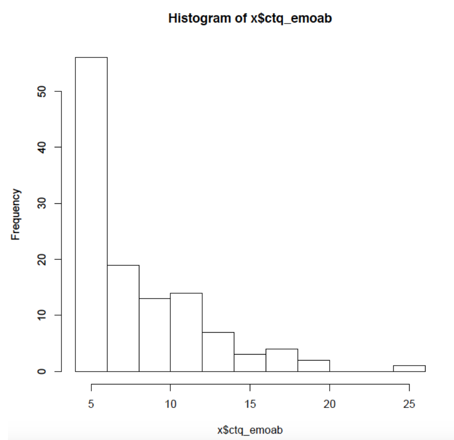

Figure 3.3: Emotional Abuse Hisogram

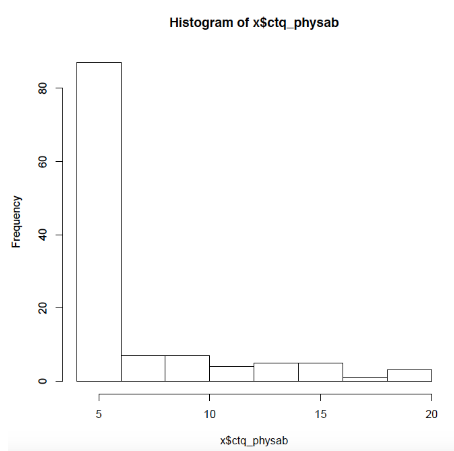

Figure 3.4: Physical Abuse Hisogram

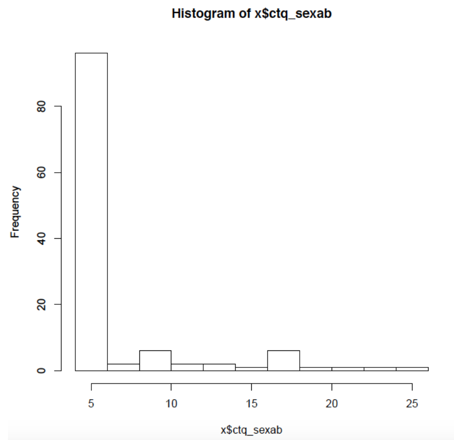

Figure 3.5: Sexual Abuse Hisogram

- Subcortical Regions: Volumes of 62 subcortical regions are in our dataset.
- Cortical Regions: Thickness, area and volume of about 150 regions (total of 448 features) are also available in this data.
- Other SES data: Later during the research, I were also given some socio-economical status data such as IQ score, marital status, maximum education and number of adults with income at home.

3.2 fMRI Data

I also have a relatively small fMRI data which is only available in $Study2$. The features in this data are right and left Amygdala reactivity and internalizing and externalizing symptoms score.

Chapter 4
RESULTS: VISUALIZATION

In this chapter, I show all results that were driven in a visual form. I focus on heatmaps and PCA plots. In the first to third sections, I present results for classifying child maltreatment, gender and age, respectively. The final section, is discussion about the results on what can be driven from them.

4.1 Classifying Child Maltreatment

Classification of child maltreatment is the main focus of this thesis. Because of that, most of the results are also focus in this section. I have a lot of results from sMRI data and minimal results for the fMRI data, given in the following subsections:

4.1.1 sMRI Data

There are many dimensions to our visualization results for child maltreatment classification. One dimension is the visual form itself, namely heatmap and PCA plot. Another dimension, is different subsets of samples such as considering all samples, only one study or only one gender in our dataset. Yet another dimension, is the choice of features to consider: all features, only subcortial volumes or only considering thickness, area or volume of cortical regions. All of these give us 50 outcomes to consider.

Out of all outcomes, I can easily acknowledge the signal in the sMRI dataset. Some of the strongest signals in the heatmaps are provided in the following figures. The rows are samples and the columns are features. The blue and yellow ribbons shows the control and maltreated groups, respectively:

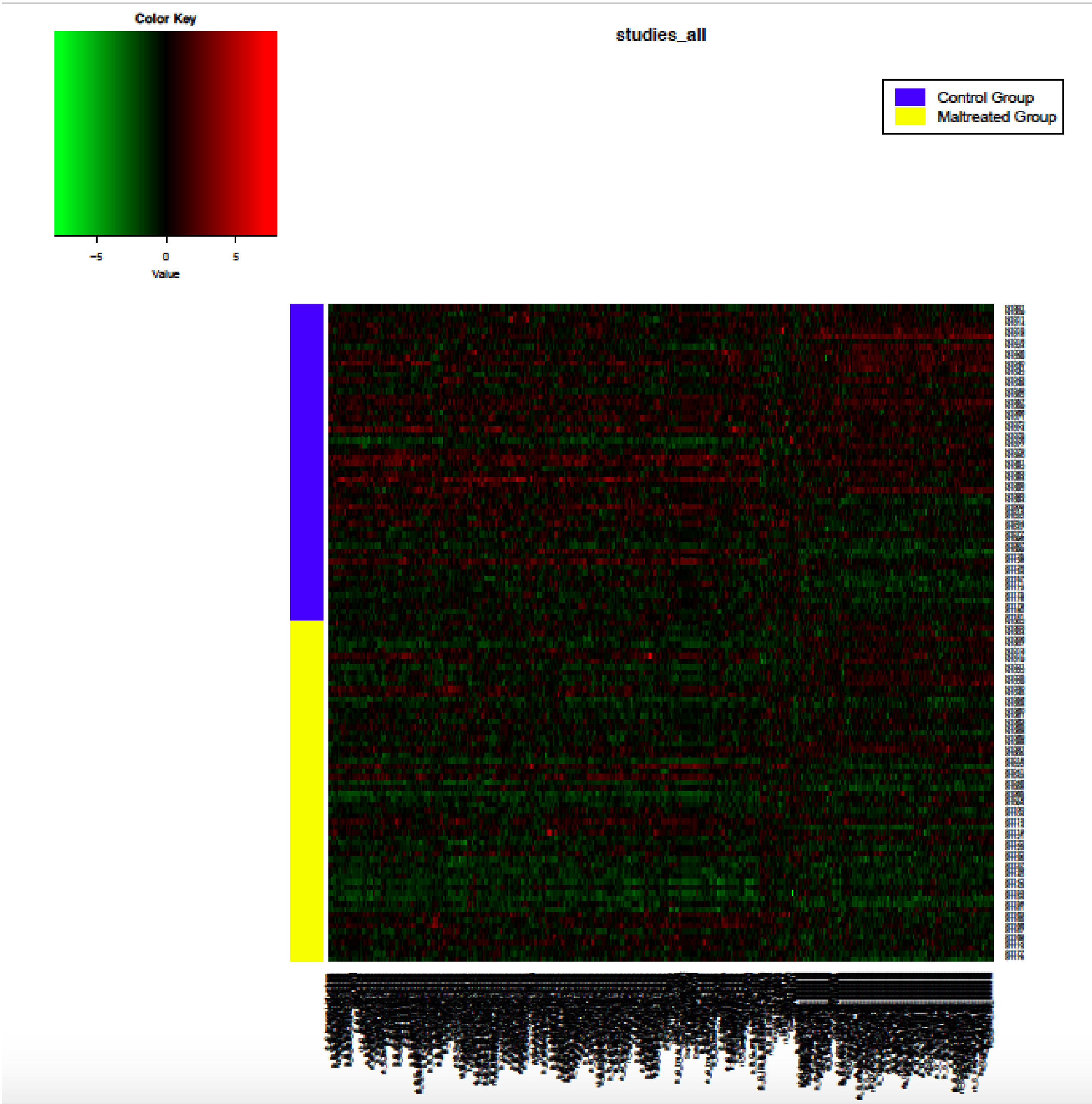

Figure 4.1: Heatmap for Child Maltreatment Classification Using All the Data

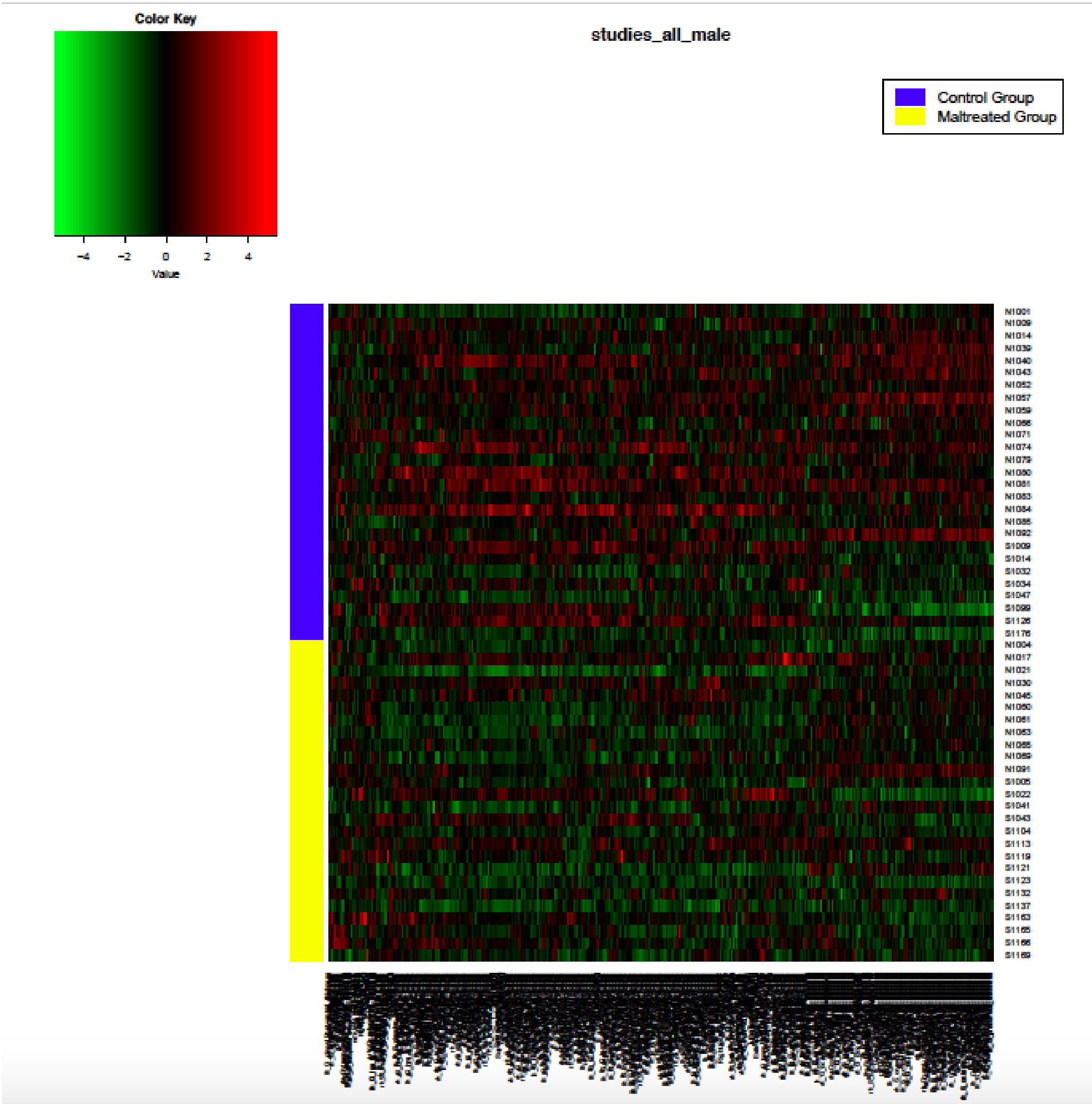

Figure 4.2: Heatmap for Child Maltreatment Classification Considering Male Samples

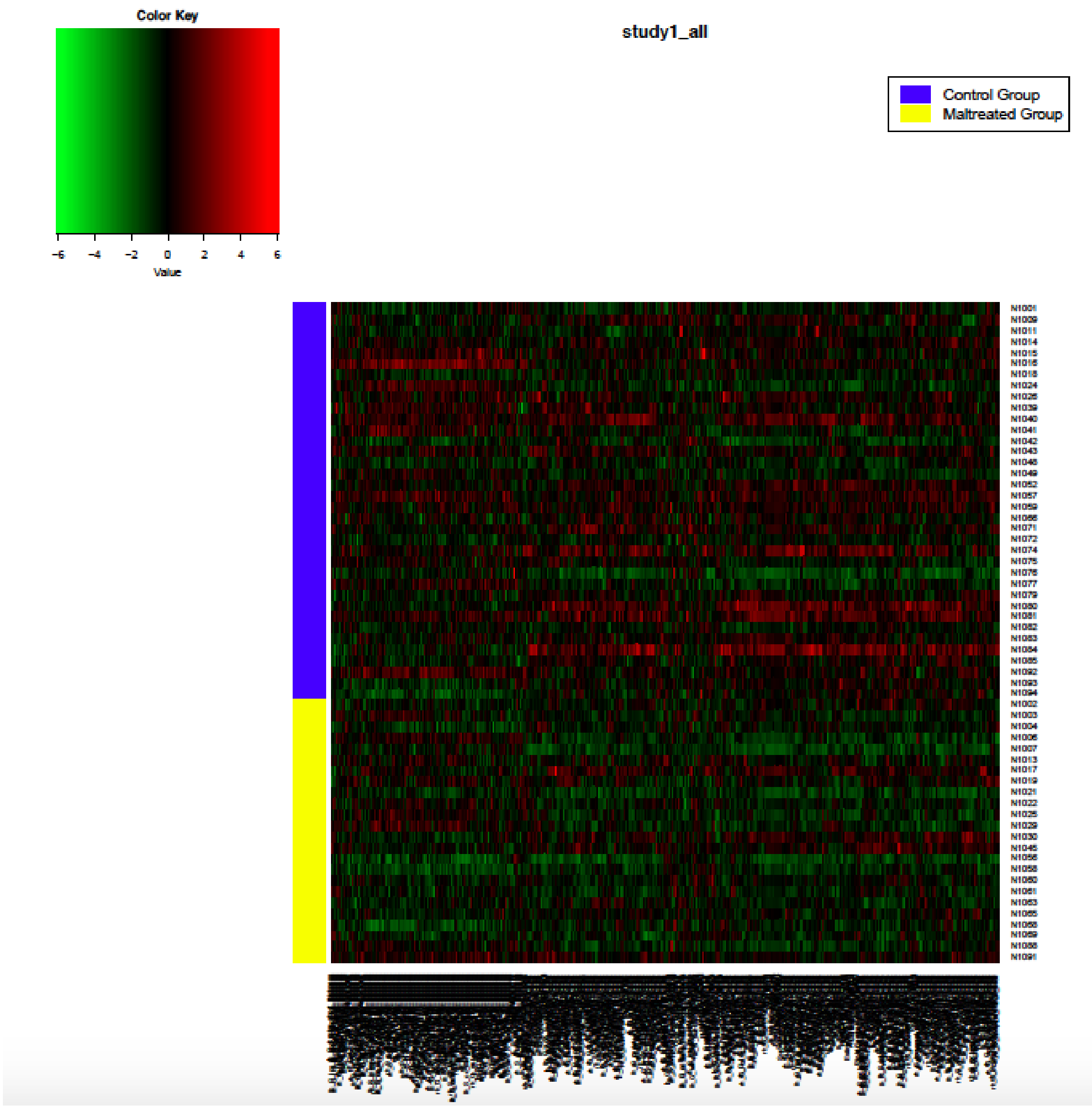

Figure 4.3: Heatmap for Child Maltreatment Classification Considering Study1

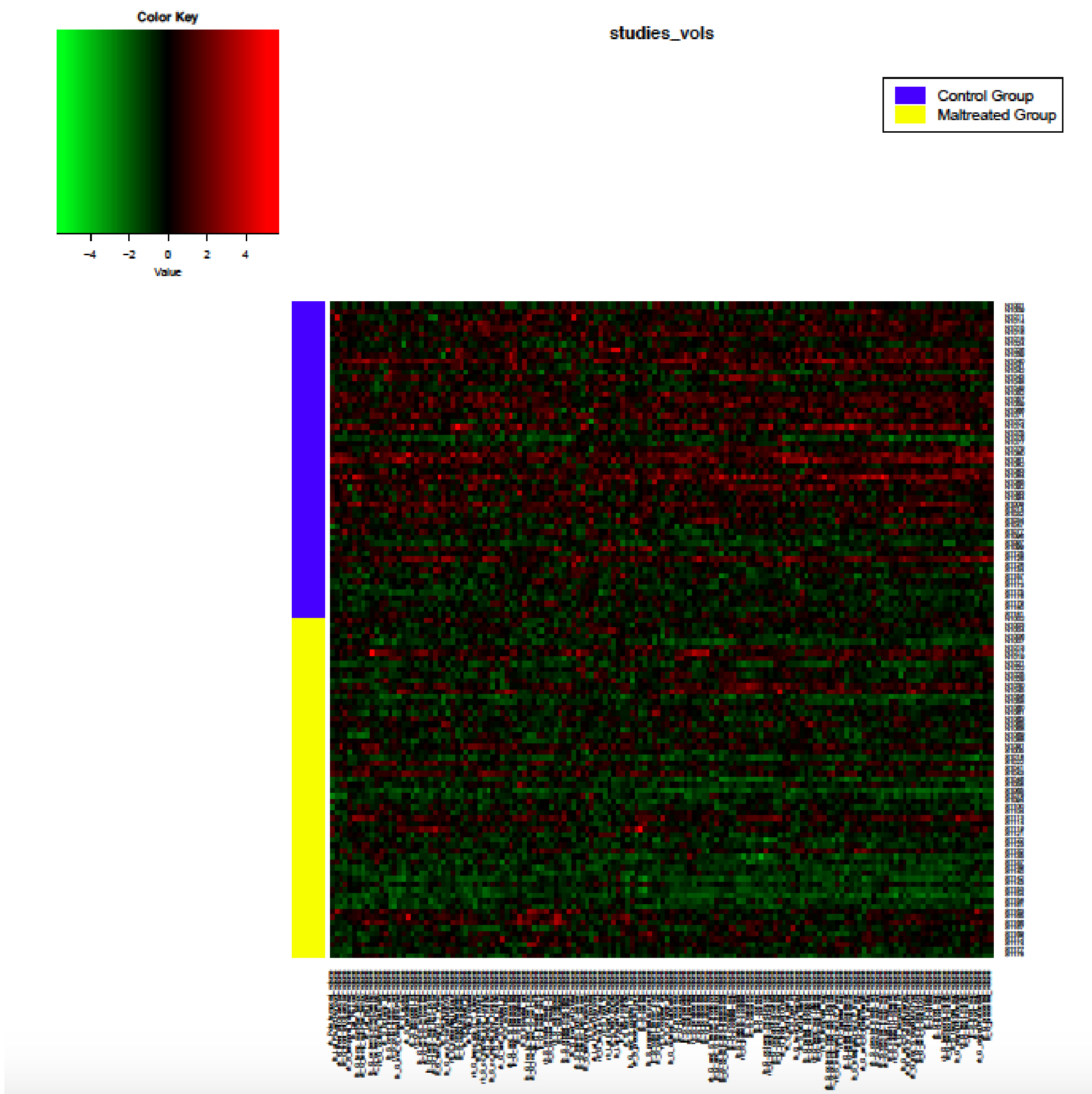

Figure 4.4: Heatmap for Child Maltreatment Classification Considering Volumes of Cortical Regions

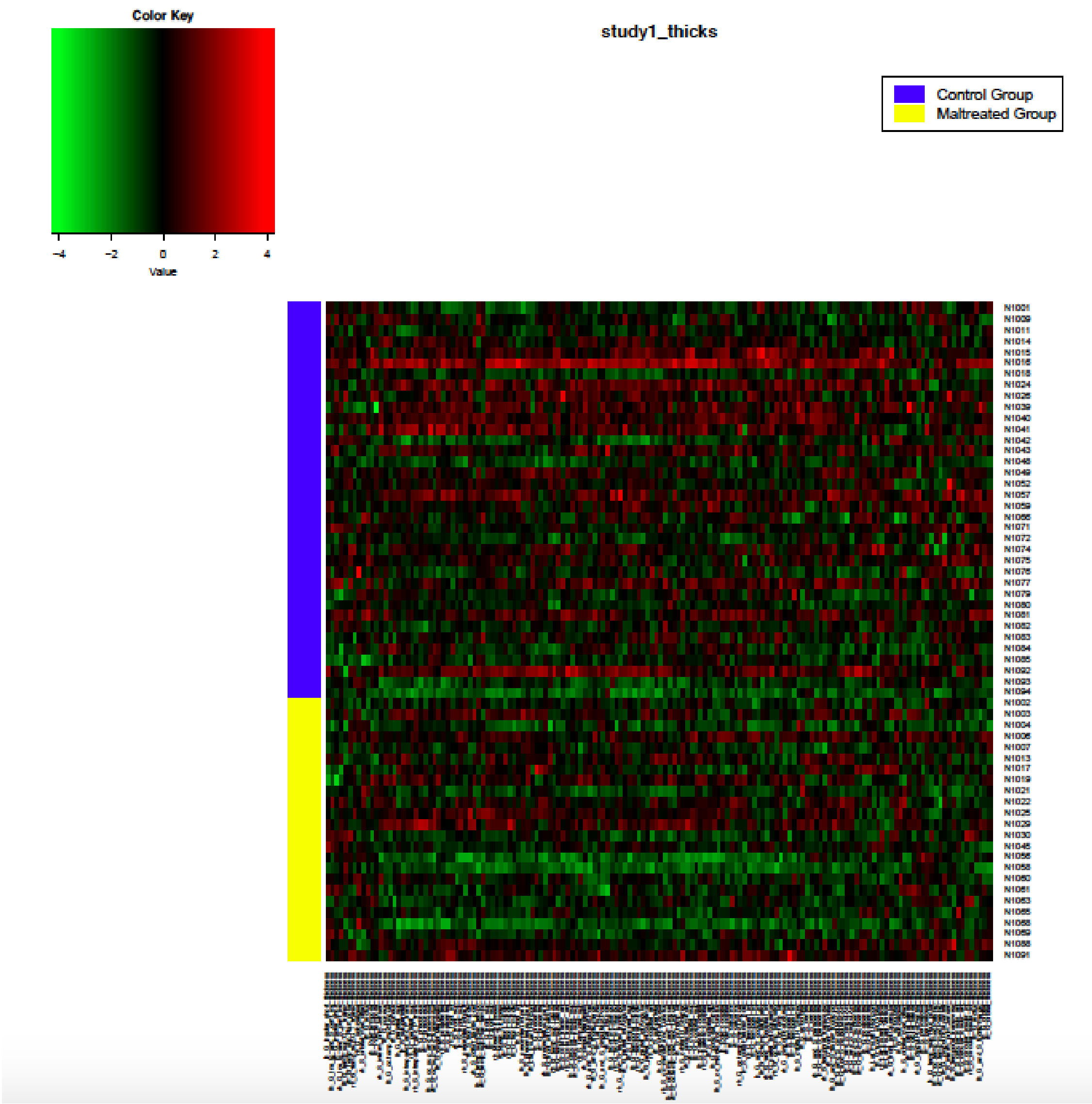

Figure 4.5: Heatmap for Child Maltreatment Classification Considering Only Thickness of Cortical Regions in Study1

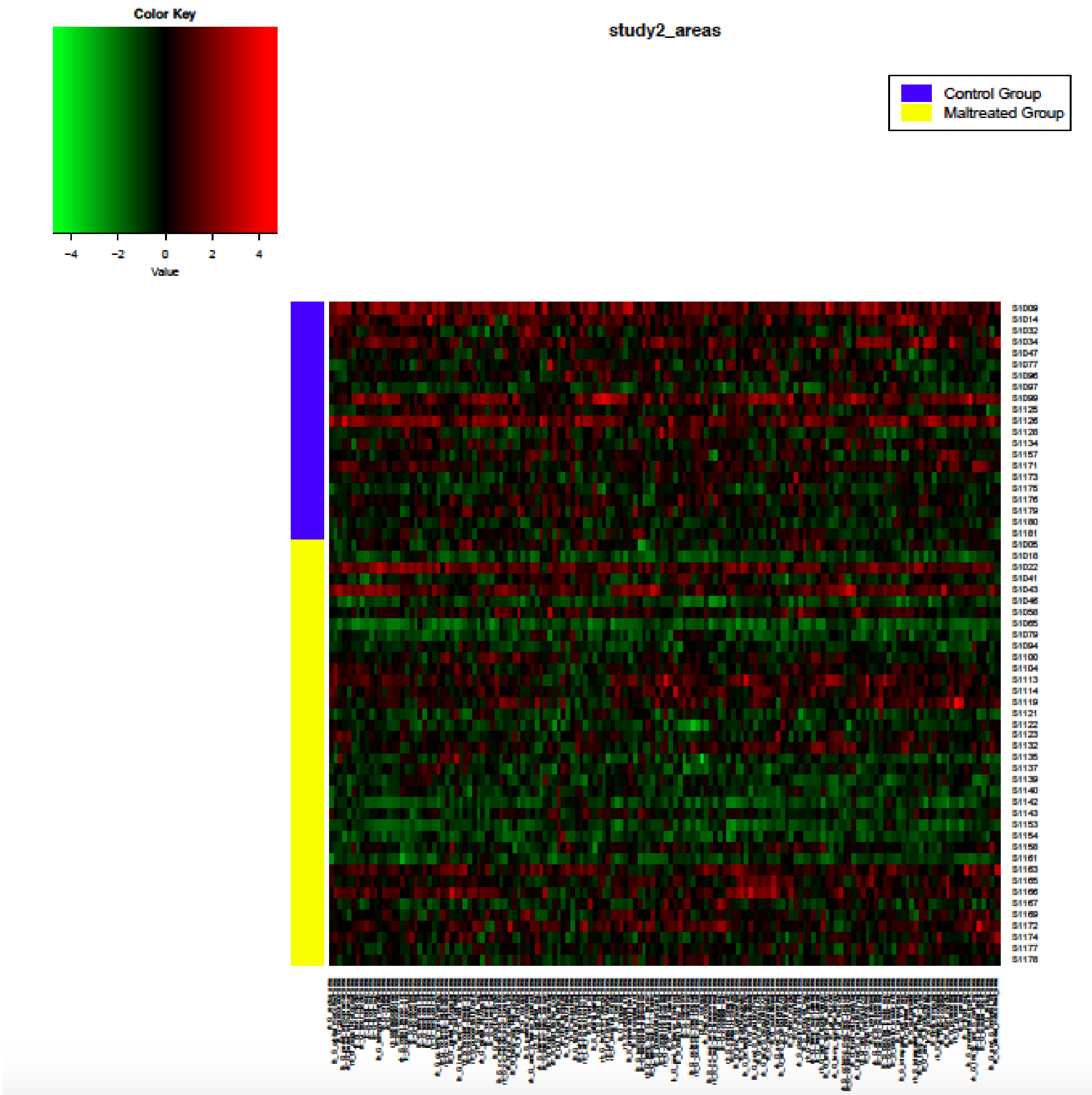

Figure 4.6: Heatmap for Child Maltreatment Classification Considering Only Area of Cortical Regions in Study2

As mentioned in Chapter 2, PCA or principal component analysis tries to reduce the dimensions of the input data by mapping the features to several principal components that each explain the variability of the data in one dimension. PCA plots shown below, map the input data to two dimensions meaning only showing the two most important components of the data. The percentage shown in each dimension, means what percentage of the variability of the data is explained through that component. The light blue dots denote the control group and the dark blue ones denote the maltreated group:

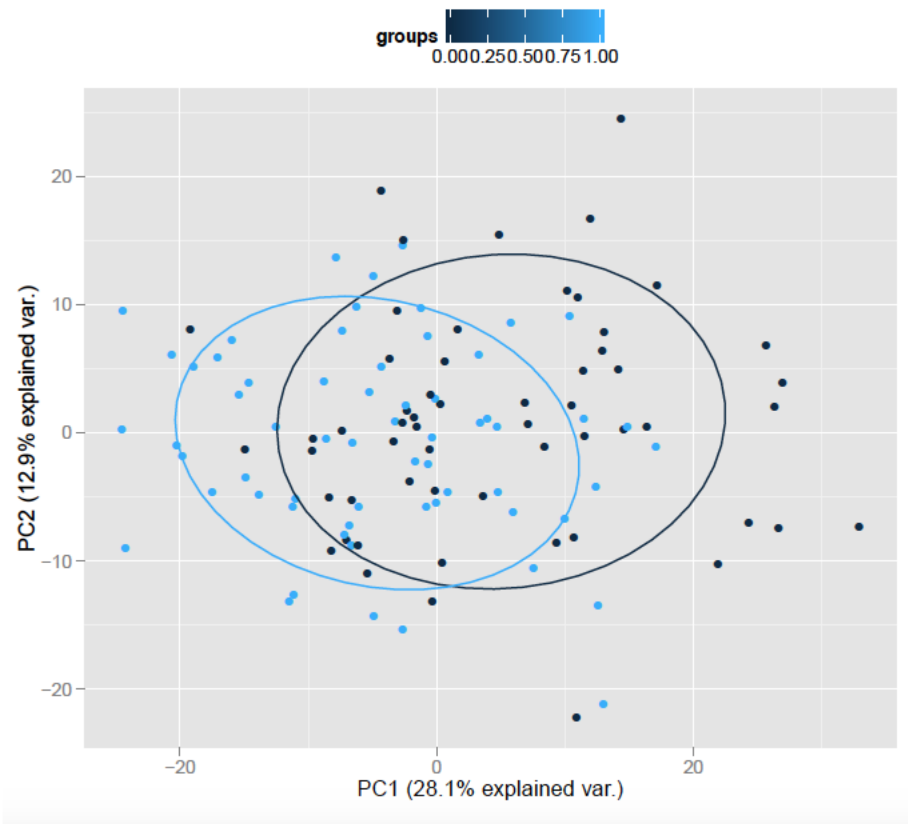

Figure 4.7: PCA for Child Maltreatment Classification

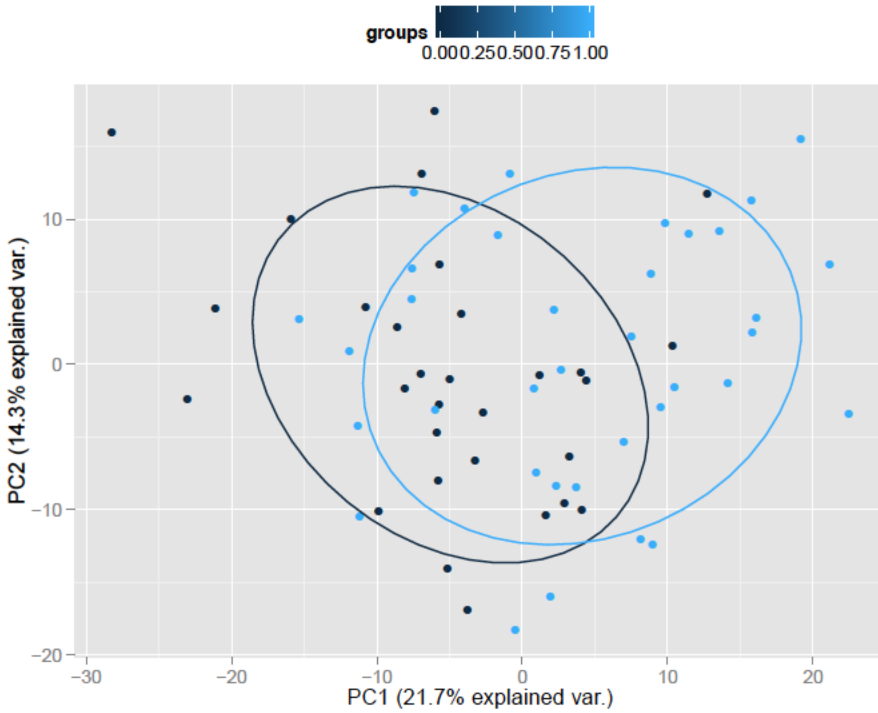

Figure 4.8: PCA for Child Maltreatment Classification Considering Female Samples

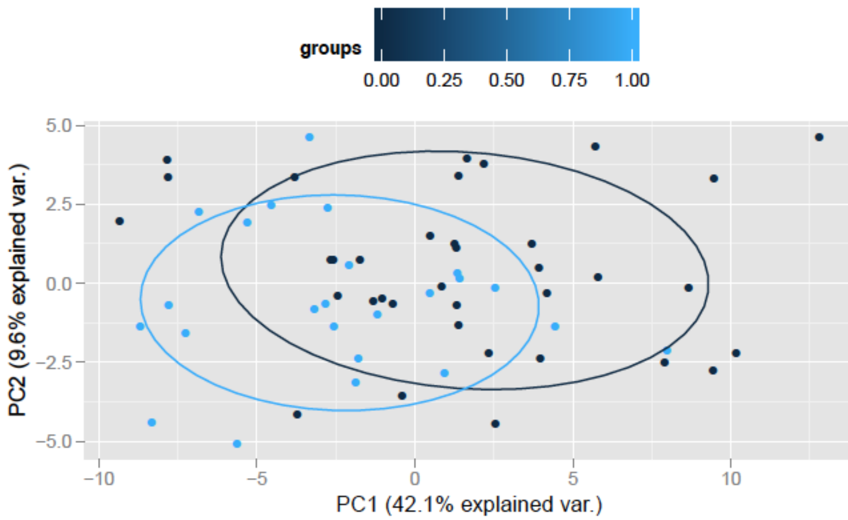

Figure 4.9: PCA for Child Maltreatment Classification Considering Only Subcortical Regions in Study1

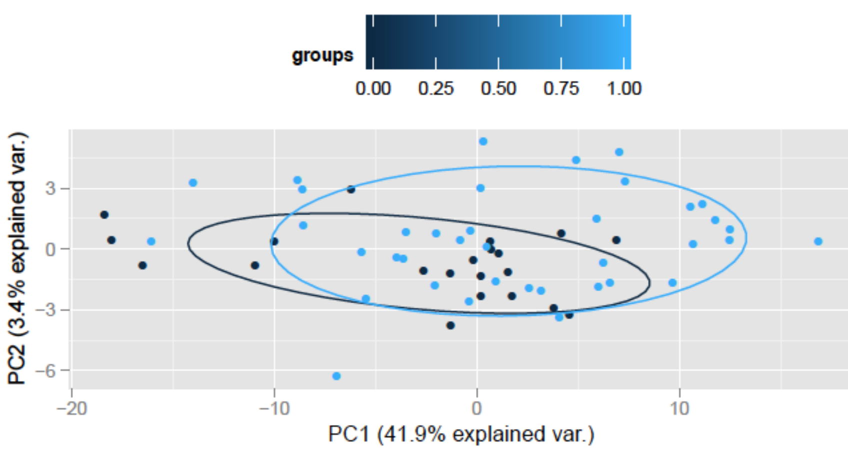

Figure 4.10: PCA for Child Maltreatment Classification Considering Only Cortical Areas in Study2

4.1.2 fMRI Data

In the fMRI data, The main features are internalizing and externalizing symptoms score and left and right Amygdala reactivity score. To see how these four features contribute to the variability of the fMRI data, I have also included these features in the Figure 4.11:

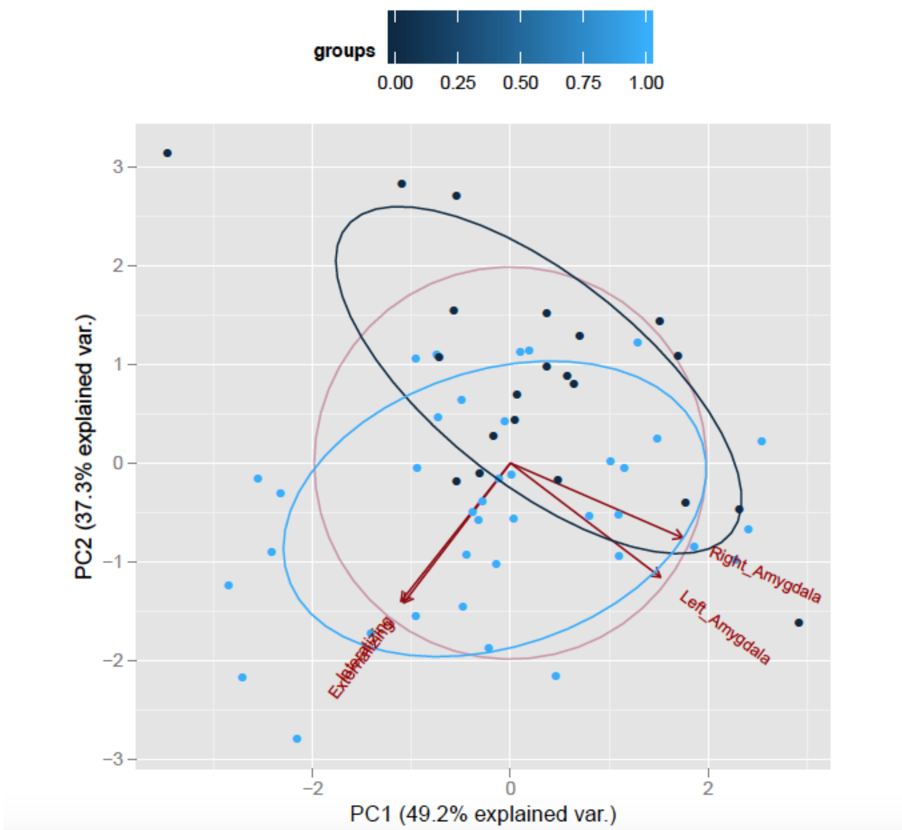

Figure 4.11: PCA for Child Maltreatment Classification Considering fMRI Data

4.2 Classifying Gender

Although our main results lie within classifying child trauma, I decided to try classifying other features that were in the dataset. I started by prediction of gender. Interestingly, I can see a signal for this feature in the following heatmap and PCA plot:

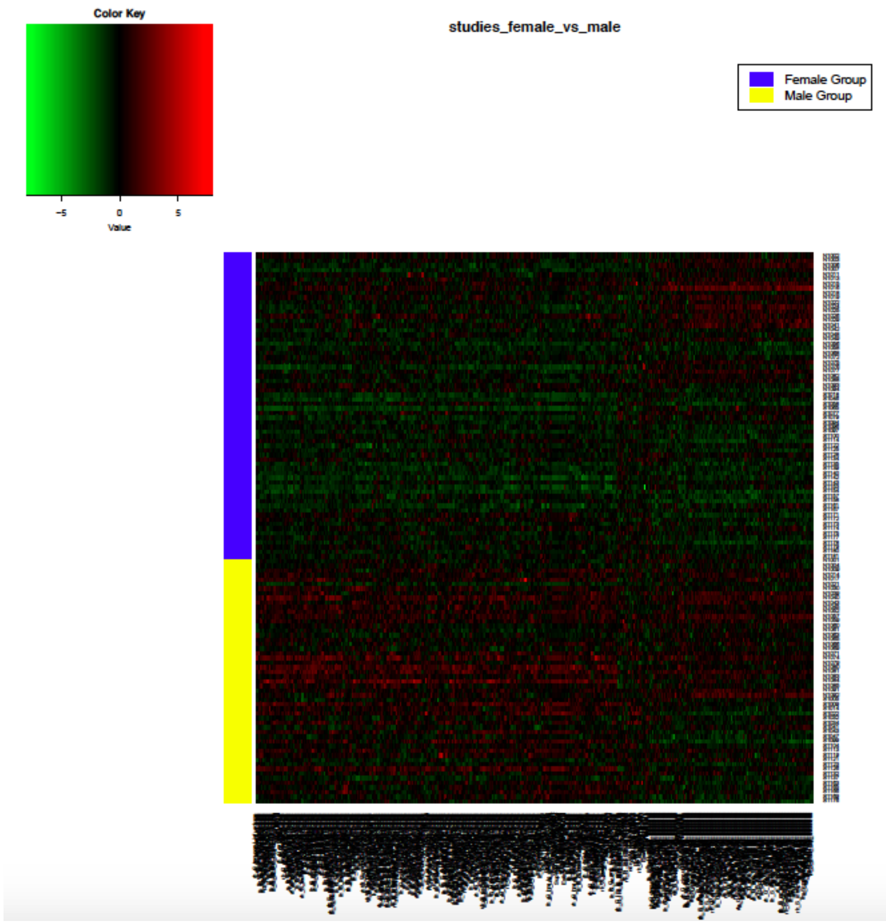

Figure 4.12: Heatmap for Gender Classification

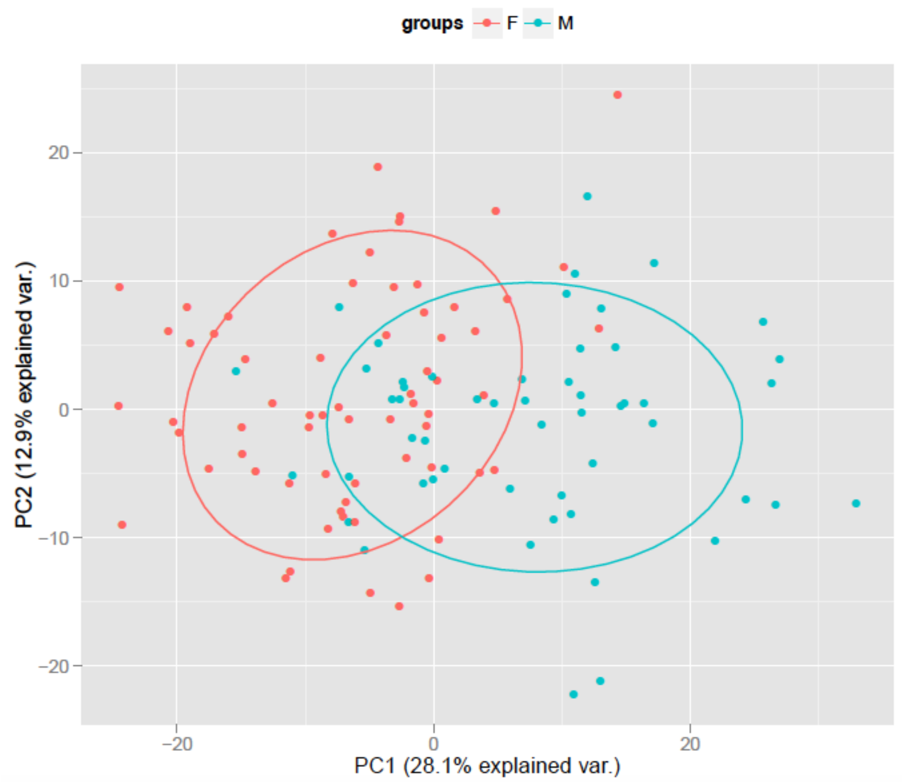

Figure 4.13: PCA for Gender Classification

4.3 Classifying Age

I then turned to age. Since the ages given in the dataset were continuous from age of 8 to 20, I try to see if by sorting the data by age, a heatmap will show us anything and also if PCA plots can find principal components that could help with dimension reduction:

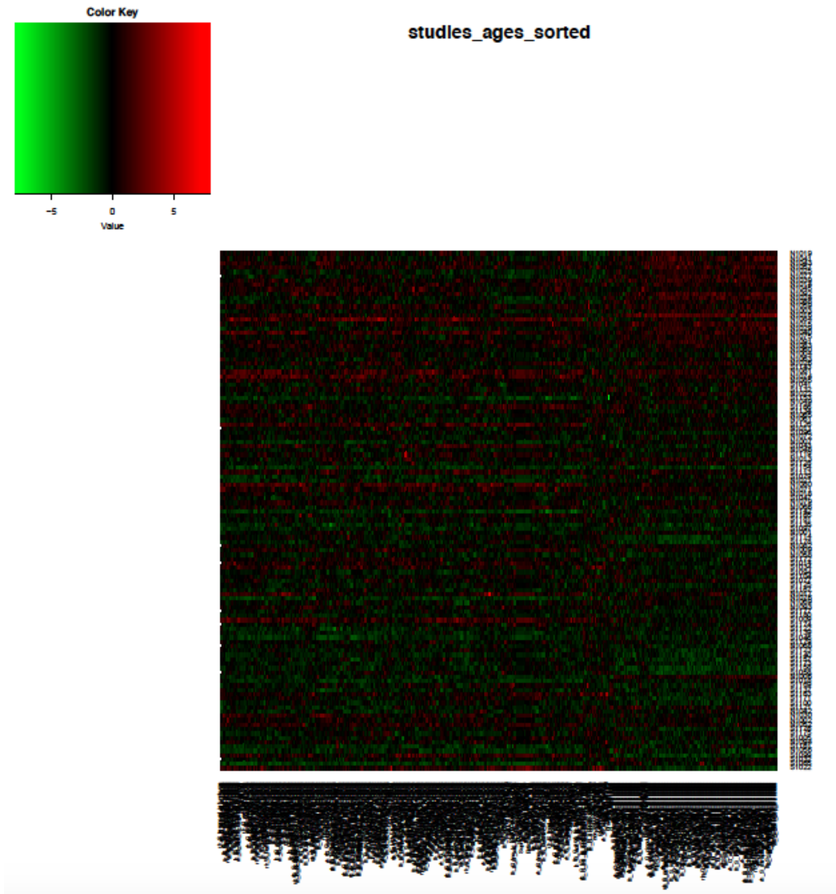

Figure 4.14: Heatmap for Age Regression (Samples are sorted by their ages)

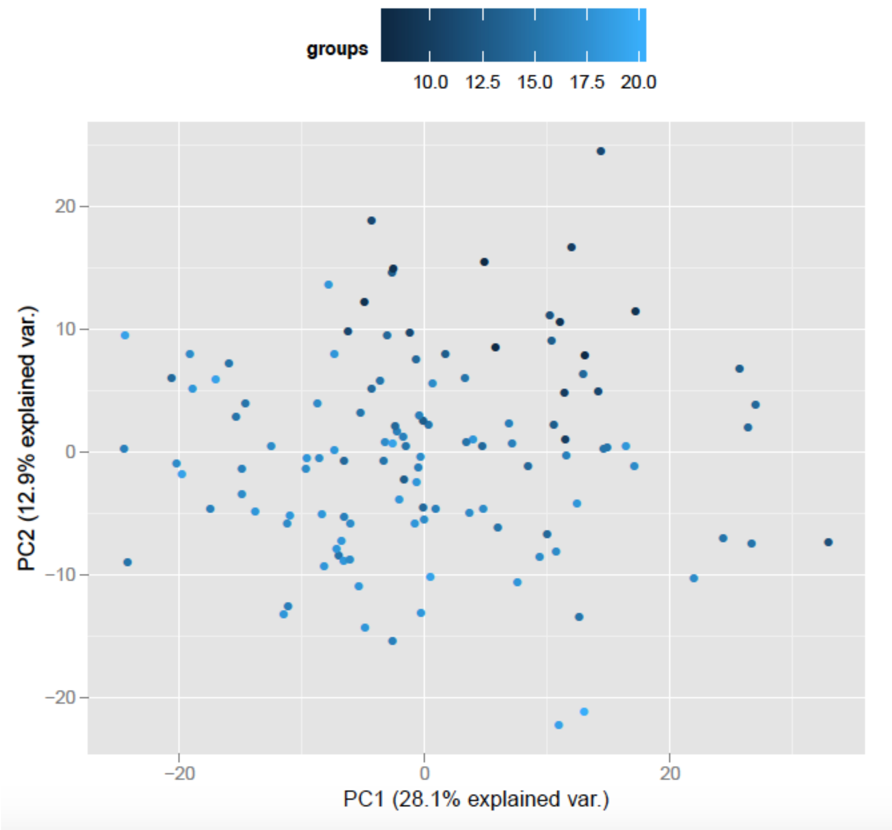

Figure 4.15: PCA for Age Regression (Dark blue dots denote younger ages and light blue denote older ages)

4.4 Discussion

In this section, I try to explain the visualization results. I have tried many approaches and techniques so that our heatmaps and PCA plots could show as much signal as possible. I mention some of them here:

- Other than the binary feature stating the maltreatment, as mentioned in Section 3.1, I have three features showing different abuse type degrees. I also visualized these three features. The signal for these features was not as obvious as maltreatment status feature itself.

- There is an obvious difference between thickness values between Study1 and Study2. This makes using thickness features harder in combination of studies. However, I will discuss in the next chapter that how the thickness seems to be the most important identifier for classifying child maltreatment.

- Gender and age contributes to brain size and structure. There is a lot mentioned in the literature on the importance of gender and age in the brain maturation. For example, in Figure 4.16 from Giedd and Rapoport's paper [18], I can see the difference. This also signals that separating the data in age buckets and considering each gender separately for child maltreatment classification, might be a good idea. However, since the number is samples are limited in our dataset, I don't have the luxury to do that.

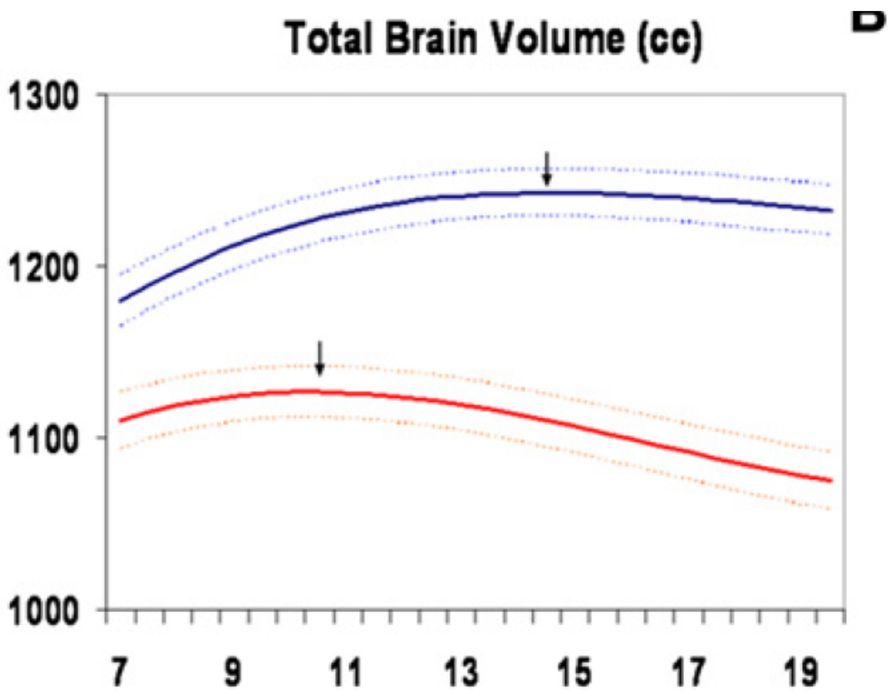

Figure 4.16: Difference in Brain Maturation Between Females (Red line) and Males (Blue line) Through Years

- Heatmaps did not show any useful signals until I scaled and centered the features by columns. In other words, I moved each column's average to zero and divided the column value by standard deviation. I also experimented with log transformation of the data (instead of value consider the log of that value). It did not add to the signal of the data. So I didn't applied it to the dataset.

Chapter 5

RESULTS: CLASSIFICATION METHODS

The main results of this thesis are mentioned in this chapter. I start by results about classification of child maltreatment. I then turn to classifying other features such as gender, age, specific abuse types, income level, IQ, marital status and education level. I then talk about feature selection on classifying child maltreatment. Finally, I discuss the results and try to make sense of the results I have gotten in this research project.

In this project I used cross validation to calculate the accuracy of our classification methods. All of our cross-validations are 10-fold.

5.1 Classifying Child Maltreatment

With 119 samples, I use 10-fold cross validation to identify subsets of features that are predictive of child maltreatment. Since I observed differences between male and female brain structure in the visualization results in Figure 4.12, I also considered gender as a factor. Also, since the data is a combination of two studies, I can also assume that there are differences in data between the studies.

As with the features, it is predictable that thickness, area and volume of a cortical region would be correlated. Thus, using all of them would increase the chance of over-fitting. Therefore, apart from considering all features at the same time, I also consider each category of features independently.

More precisely, for training and testing samples I have considered these options:

1. All→CV: All samples using cross validation

2. S1→S2: Study1 as training data and Study2 as test data

3. S2→S1: Study2 as training data and Study1 as test data

4. S1→CV: Study1 samples using cross validation

5. S2→CV: Study2 samples using cross validation

6. M→F: Male samples as training data and female samples as test data

7. F→M: Female samples as training data and male samples as test data

8. M→CV: Male samples using cross validation

9. F→CV: Female samples using cross validation

And for the feature selection step, I explored these options:

1. All: All features

2. Sub: Subcortical volumes features

3. Area: Cortical area features

4. Thick: Cortical thickness features

5. Vol: Cortical volumes features

And finally for the classification methods, I empirically studied these methods that are explained in detail in Section 2.3:

- Random Forest (RF)

- XGBoost

- Random Uniform Forest (RUF)

- Generalized Linear Model (GLM)
- Support Vector Machine (SVM)
- Recursive Partitioning and Regression Trees (RPART)
- Least Absolute Shrinkage and Selection Operator (LASSO)
- Bayesian Model Averaging (BMA)
- Ensemble Model of Random Forest and LASSO

The following tables show the accuracy results of these methods for all sample and feature options. I will discuss these tables in detail in Section 5.4:

	All→CV	S1→S2	S2→S1	S1→CV	S2→CV	M→F	F→M	M→CV	F→CV
All	0.63	0.61	0.61	0.62	0.58	0.57	0.62	0.73	0.66
Sub	0.68	0.65	0.59	0.69	0.64	0.59	0.63	0.67	0.71
Area	0.61	0.53	0.51	0.65	0.62	0.57	0.58	0.69	0.61
Thick	0.61	0.60	0.45	0.52	0.59	0.52	0.59	0.65	0.61
Vol	0.63	0.61	0.65	0.65	0.57	0.57	0.60	0.75	0.67

Table 5.1: Accuracy of Random Forest for Classifying Child Maltreatment. Rows denote the initial features that are chosen (All: All features, Sub: Subcortical regions, Area: Cortical areas, Thick: Cortical thicknesses, Vol: Cortical volumes). Columns in the table denote which set of samples were chosen for training and which was chosen for testing. CV stands for cross-validation and means the sample set uses cross validation for training and testing. In other cases, the left set of samples are for training the the right set is for testing (All: All samples, S1: Study1, S2: Study2, M: Male samples, F: Female samples). Numbers are accuracies: what ratio of predictions were correct (true positive and true negative)

	All→CV	S1→S2	S2→S1	S1→CV	S2→CV	M→F	F→M	M→CV	F→CV
All	0.60	0.59	0.67	0.54	0.52	0.47	0.62	0.63	0.62
Sub	0.60	0.41	0.62	0.60	0.61	0.62	0.53	0.51	0.63
Area	0.54	0.59	0.53	0.50	0.55	0.55	0.47	0.62	0.52
Thick	0.53	0.58	0.48	0.50	0.59	0.48	0.57	0.58	0.54
Vol	0.62	0.53	0.58	0.57	0.51	0.56	0.66	0.67	0.63

Table 5.2: Accuracy of XGBoost for Classifying Child Maltreatment. Rows denote the initial features that are chosen (All: All features, Sub: Subcortical regions, Area: Cortical areas, Thick: Cortical thicknesses, Vol: Cortical volumes). Columns in the table denote which set of samples were chosen for training and which was chosen for testing. CV stands for cross-validation and means the sample set uses cross validation for training and testing. In other cases, the left set of samples are for training the the right set is for testing (All: All samples, S1: Study1, S2: Study2, M: Male samples, F: Female samples). Numbers are accuracies: what ratio of predictions were correct (true positive and true negative)

	All→CV	S1→S2	S2→S1	S1→CV	S2→CV	M→F	F→M	M→CV	F→CV
All	0.62	0.60	0.56	0.62	0.49	0.58	0.62	0.70	0.64
Sub	0.67	0.60	0.56	0.70	0.58	0.59	0.61	0.63	0.70
Area	0.62	0.52	0.48	0.64	0.55	0.53	0.62	0.67	0.59
Thick	0.59	0.58	0.42	0.50	0.45	0.53	0.58	0.62	0.60
Vol	0.62	0.59	0.62	0.66	0.46	0.57	0.61	0.72	0.65

Table 5.3: Accuracy of Random Uniform Forest for Classifying Child Maltreatment. Rows denote the initial features that are chosen (All: All features, Sub: Subcortical regions, Area: Cortical areas, Thick: Cortical thicknesses, Vol: Cortical volumes). Columns in the table denote which set of samples were chosen for training and which was chosen for testing. CV stands for cross-validation and means the sample set uses cross validation for training and testing. In other cases, the left set of samples are for training the the right set is for testing (All: All samples, S1: Study1, S2: Study2, M: Male samples, F: Female samples). Numbers are accuracies: what ratio of predictions were correct (true positive and true negative)

	All→CV	S1→S2	S2→S1	S1→CV	S2→CV	M→F	F→M	M→CV	F→CV
All	0.51	0.66	0.52	0.51	0.51	0.47	0.47	0.49	0.53
Sub	0.60	0.66	0.52	0.50	0.52	0.47	0.42	0.52	0.53
Area	0.49	0.51	0.47	0.52	0.50	0.50	0.47	0.53	0.51
Thick	0.47	0.37	0.55	0.51	0.46	0.56	0.45	0.51	0.49
Vol	0.49	0.46	0.45	0.49	0.50	0.45	0.47	0.52	0.55

Table 5.4: Accuracy of GLM for Classifying Child Maltreatment. Rows denote the initial features that are chosen (All: All features, Sub: Subcortical regions, Area: Cortical areas, Thick: Cortical thicknesses, Vol: Cortical volumes). Columns in the table denote which set of samples were chosen for training and which was chosen for testing. CV stands for cross-validation and means the sample set uses cross validation for training and testing. In other cases, the left set of samples are for training the the right set is for testing (All: All samples, S1: Study1, S2: Study2, M: Male samples, F: Female samples). Numbers are accuracies: what ratio of predictions were correct (true positive and true negative)

	All→CV	S1→S2	S2→S1	S1→CV	S2→CV	M→F	F→M	M→CV	F→CV
All	0.61	0.58	0.60	0.60	0.41	0.58	0.53	0.71	0.62
Sub	0.61	0.46	0.60	0.76	0.57	0.53	0.55	0.63	0.67
Area	0.62	0.53	0.60	0.65	0.63	0.53	0.51	0.64	0.59
Thick	0.59	0.42	0.60	0.53	0.38	0.53	0.51	0.62	0.61
Vol	0.61	0.63	0.60	0.62	0.54	0.59	0.60	0.72	0.62

Table 5.5: Accuracy of SVM for Classifying Child Maltreatment. Rows denote the initial features that are chosen (All: All features, Sub: Subcortical regions, Area: Cortical areas, Thick: Cortical thicknesses, Vol: Cortical volumes). Columns in the table denote which set of samples were chosen for training and which was chosen for testing. CV stands for cross-validation and means the sample set uses cross validation for training and testing. In other cases, the left set of samples are for training the the right set is for testing (All: All samples, S1: Study1, S2: Study2, M: Male samples, F: Female samples). Numbers are accuracies: what ratio of predictions were correct (true positive and true negative)

	All→CV	S1→S2	S2→S1	S1→CV	S2→CV	M→F	F→M	M→CV	F→CV
All	0.59	0.46	0.53	0.57	0.52	0.44	0.62	0.55	0.57
Sub	0.57	0.51	0.60	0.60	0.56	0.64	0.55	0.48	0.62
Area	0.55	0.37	0.57	0.62	0.53	0.62	0.40	0.55	0.52
Thick	0.50	0.34	0.48	0.51	0.51	0.33	0.53	0.64	0.46
Vol	0.58	0.51	0.65	0.58	0.52	0.62	0.70	0.58	0.56

Table 5.6: Accuracy of RPART for Classifying Child Maltreatment. Rows denote the initial features that are chosen (All: All features, Sub: Subcortical regions, Area: Cortical areas, Thick: Cortical thicknesses, Vol: Cortical volumes). Columns in the table denote which set of samples were chosen for training and which was chosen for testing. CV stands for cross-validation and means the sample set uses cross validation for training and testing. In other cases, the left set of samples are for training the the right set is for testing (All: All samples, S1: Study1, S2: Study2, M: Male samples, F: Female samples). Numbers are accuracies: what ratio of predictions were correct (true positive and true negative)

	All→CV	S1→S2	S2→S1	S1→CV	S2→CV	M→F	F→M	M→CV	F→CV
All	0.66	0.59	0.60	0.74	0.79	0.64	0.72	0.68	0.67
Sub	0.74	0.64	0.70	0.79	0.69	0.67	0.70	0.67	0.76
Area	0.67	0.54	0.60	0.77	0.75	0.59	0.68	0.61	0.63
Thick	0.70	0.56	0.60	0.72	0.67	0.62	0.64	0.67	0.67
Vol	0.72	0.54	0.62	0.77	0.72	0.64	0.72	0.71	0.67

Table 5.7: Accuracy of LASSO for Classifying Child Maltreatment. Rows denote the initial features that are chosen (All: All features, Sub: Subcortical regions, Area: Cortical areas, Thick: Cortical thicknesses, Vol: Cortical volumes). Columns in the table denote which set of samples were chosen for training and which was chosen for testing. CV stands for cross-validation and means the sample set uses cross validation for training and testing. In other cases, the left set of samples are for training the the right set is for testing (All: All samples, S1: Study1, S2: Study2, M: Male samples, F: Female samples). Numbers are accuracies: what ratio of predictions were correct (true positive and true negative)

	All→CV	S1→S2	S2→S1	S1→CV	S2→CV	M→F	F→M	M→CV	F→CV
All	NA	0.59	0.62	0.57	0.56	0.61	0.64	NA	NA
Sub	NA	NA	0.63	NA	NA	NA	NA	NA	NA
Area	0.60	0.58	0.48	0.62	0.64	0.50	0.70	0.57	0.56
Thick	0.59	0.56	0.60	0.57	0.71	0.53	0.51	0.64	0.41
Vol	0.62	0.59	0.62	0.63	0.64	0.61	0.64	0.66	0.62

Table 5.8: Accuracy of BMA for Classifying Child Maltreatment. Rows denote the initial features that are chosen (All: All features, Sub: Subcortical regions, Area: Cortical areas, Thick: Cortical thicknesses, Vol: Cortical volumes). Columns in the table denote which set of samples were chosen for training and which was chosen for testing. CV stands for cross-validation and means the sample set uses cross validation for training and testing. In other cases, the left set of samples are for training the the right set is for testing (All: All samples, S1: Study1, S2: Study2, M: Male samples, F: Female samples). Numbers are accuracies: what ratio of predictions were correct (true positive and true negative)

	All→CV	S1→S2	S2→S1	S1→CV	S2→CV	M→F	F→M	M→CV	F→CV
All	0.62	0.59	0.44	0.61	0.63	0.58	0.68	0.69	0.65
Sub	0.67	0.64	0.64	0.65	0.56	0.64	0.62	0.62	0.69
Area	0.61	0.48	0.46	0.59	0.60	0.53	0.62	0.65	0.58
Thick	0.58	0.57	0.60	0.54	0.55	0.49	0.61	0.62	0.58
Vol	0.62	0.59	0.65	0.65	0.62	0.57	0.61	0.74	0.63

Table 5.9: Accuracy of Ensemble Model of Random Forest and LASSO for Classifying Child Maltreatment. Rows denote the initial features that are chosen (All: All features, Sub: Subcortical regions, Area: Cortical areas, Thick: Cortical thicknesses, Vol: Cortical volumes). Columns in the table denote which set of samples were chosen for training and which was chosen for testing. CV stands for cross-validation and means the sample set uses cross validation for training and testing. In other cases, the left set of samples are for training the the right set is for testing (All: All samples, S1: Study1, S2: Study2, M: Male samples, F: Female samples). Numbers are accuracies: what ratio of predictions were correct (true positive and true negative)

5.2 Classifying Other Features

I now show the results on classifying features other than child maltreatment. These features are gender, age, abuse types, parents with income, IQ, marital status and education level of parents.

I only used LASSO and Random Forest in this section, since it gave us the best results in Section 5.1. I will discuss results from there along with results from this section in Section 5.4. I also divided the features into two parts in this section: Subcortical and Cortical regions. As for samples, I considered combined studies, each study individually, and each gender individually (except when predicting the gender itself). For sample I used these samples both in training and test phases using 10-fold cross validation.

5.2.1 *Gender*

The results for classifying gender are given in Tables 5.10 and 5.11.

	All→CV	S1→CV	S2→CV
Cortical	0.77	0.67	0.78
Subcortical	0.80	0.70	0.78

Table 5.10: Classifying Gender using LASSO Method. Each row denotes which features were considered: Cortical or Subcortical regions of the brain. We used 10-fold cross-validation for the results of this table. Columns denote which set of samples were chosen (All: All samples, S1: Study1, S2: Study2). Numbers accuracies: the ratio of correct predictions (positive or negative)

	All→CV	S1→CV	S2→CV
Cortical	0.77	0.70	0.80
Subcortical	0.81	0.73	0.78

Table 5.11: Classifying Gender using Random Forest Method. Each row denote which features were considered: Cortical or Subcortical regions of the brain. We used 10-fold cross-validation for the results of this table. Columns denote which set of samples were chosen (All: All samples, S1: Study1, S2: Study2). Numbers accuracies: the ratio of correct predictions (positive or negative)

5.2.2 *Age*

Since age is not a binary feature, I divided age into 3 categories, age less than 14, age between 14 and 17, and age older than 17. Then I try to classify patients in one of these categories with respect to other two categories. The results for classifying gender is given below.

	All→CV	S1→CV	S2→CV	M→CV	F→CV
Cortical	0.90	0.92	NA	0.75	0.91
Subcortical	0.87	0.83	NA	0.75	0.88

Table 5.12: Classifying Children Under 14 using LASSO Method. Each row denote which features were considered: Cortical or Subcortical regions of the brain. We used 10-fold cross-validation for the results of this table. Columns denote which set of samples were chosen (All: All samples, S1: Study1, S2: Study2, M: Male samples, F: Female samples). Numbers accuracies: the ratio of correct predictions (positive or negative)

	All→CV	S1→CV	S2→CV	M→CV	F→CV
Cortical	0.92	0.85	NA	0.87	0.91
Subcortical	0.86	0.75	NA	0.75	0.86

Table 5.13: Classifying Children Under 14 using Random Forest Method. Each row denote which features were considered: Cortical or Subcortical regions of the brain. We used 10-fold cross-validation for the results of this table. Columns denote which set of samples were chosen (All: All samples, S1: Study1, S2: Study2, M: Male samples, F: Female samples). Numbers accuracies: the ratio of correct predictions (positive or negative)

	All→CV	S1→CV	S2→CV	M→CV	F→CV
Cortical	0.59	0.67	0.61	0.53	0.67
Subcortical	0.57	0.67	0.42	0.55	0.58

Table 5.14: Classifying Adolescents Between 14 and 17 using LASSO Method. Each row denote which features were considered: Cortical or Subcortical regions of the brain. We used 10-fold cross-validation for the results of this table. Columns denote which set of samples were chosen (All: All samples, S1: Study1, S2: Study2, M: Male samples, F: Female samples). Numbers accuracies: the ratio of correct predictions (positive or negative)

	All→CV	S1→CV	S2→CV	M→CV	F→CV
Cortical	0.53	0.52	0.54	0.53	0.48
Subcortical	0.53	0.63	0.53	0.53	0.44

Table 5.15: Classifying Adolescents Between 14 and 17 using Random Forest Method. Each row denote which features were considered: Cortical or Subcortical regions of the brain. We used 10-fold cross-validation for the results of this table. Columns denote which set of samples were chosen (All: All samples, S1: Study1, S2: Study2, M: Male samples, F: Female samples). Numbers accuracies: the ratio of correct predictions (positive or negative)

	All→CV	S1→CV	S2→CV	M→CV	F→CV
Cortical	0.66	0.78	0.64	0.72	0.61
Subcortical	0.66	0.80	0.53	0.72	0.64

Table 5.16: Classifying Adolescents Over 17 using LASSO Method. Each row denote which features were considered: Cortical or Subcortical regions of the brain. We used 10-fold cross-validation for the results of this table. Columns denote which set of samples were chosen (All: All samples, S1: Study1, S2: Study2, M: Male samples, F: Female samples). Numbers accuracies: the ratio of correct predictions (positive or negative)

	All→CV	S1→CV	S2→CV	M→CV	F→CV
Cortical	0.68	0.80	0.54	0.72	0.58
Subcortical	0.60	0.75	0.54	0.66	0.56

Table 5.17: Classifying Adolescents Over 17 using Random Forest Method. Each row denote which features were considered: Cortical or Subcortical regions of the brain. We used 10-fold cross-validation for the results of this table. Columns denote which set of samples were chosen (All: All samples, S1: Study1, S2: Study2, M: Male samples, F: Female samples). Numbers accuracies: the ratio of correct predictions (positive or negative)

5.2.3 Abuse Types

I mentioned different abuse types available in the dataset in Section 3.1. Three kinds of abuse is reported in this dataset: emotional, physical and sexual. I classified them independently. For each abuse type, similar to age, the abuse degree is not binary, but a number between 5 and 25. I divided children into 3 categories from less severe cases to more severe cases.

I call these cases into degrees 1 to 3, 3 being the most severe cases of abuse. Then I try to classify children being abused in this degree with respect to other two degrees. In the following tables, I combined sample and feature selection and depicted them in the columns and different degrees of abuse types in the rows of the tables. As for the columns, each one is in the form of $x \to y$, where $x \in \{All, S1, S2, M, F\}$ and show all, study1, study2, male and female samples, respectively. As for the y, $y \in \{C, S\}$ where C stands for cortical and S stands for subcortical regions.

	All→C	All→S	S1→C	S1→S	S2→C	S2→S	M→C	M→S	F→C	F→S
Emotional 1	0.66	0.68	0.65	0.65	0.73	0.71	0.57	0.60	0.79	0.65
Emotional 2	0.66	0.61	0.67	0.67	0.64	0.44	0.66	0.62	0.68	0.67
Emotional 3	0.81	0.75	0.75	0.75	0.75	0.73	0.77	0.77	0.74	0.71

Table 5.18: Classifying Emotional Abuse using LASSO Method. The number in front of word "Emotional" denotes the severity of this abuse type, 1 being the least and 3 being the most severe. We choose the initial subset of samples and features that we start our training with (All: All samples, S1: Study1 samples, S2: Study2 samples, M: Male samples, F: Female samples, C: Cortical features, S: Subcortical features). The numbers in the table are accuracies (ratio of correct predictions (positive or negative)

	All→C	All→S	S1→C	S1→S	S2→C	S2→S	M→C	M→S	F→C	F→S
Emotional 1	0.68	0.61	0.65	0.52	0.73	0.68	0.55	0.49	0.71	0.64
Emotional 2	0.60	0.58	0.68	0.67	0.47	0.61	0.57	0.58	0.58	0.58
Emotional 3	0.68	0.64	0.63	0.53	0.73	0.68	0.58	0.55	0.71	0.65

Table 5.19: Classifying Emotional Abuse using Random Forest Method. The number in front of word "Emotional" denotes the severity of this abuse type, 1 being the least and 3 being the most severe. We choose the initial subset of samples and features that we start our training with (All: All samples, S1: Study1 samples, S2: Study2 samples, M: Male samples, F: Female samples, C: Cortical features, S: Subcortical features). The numbers in the table are accuracies (ratio of correct predictions (positive or negative)

	All→C	All→S	S1→C	S1→S	S2→C	S2→S	M→C	M→S	F→C	F→S
Physical 1	0.63	0.63	0.65	0.65	0.61	0.59	0.64	0.64	0.64	0.61
Physical 2	0.78	0.78	0.82	0.82	0.75	0.73	0.72	0.72	0.83	0.83
Physical 3	0.82	0.85	0.83	0.85	0.86	0.86	0.92	0.92	0.74	0.79

Table 5.20: Classifying Physical Abuse using LASSO Method. The number in front of word "Physical" denotes the severity of this abuse type, 1 being the least and 3 being the most severe. We choose the initial subset of samples and features that we start our training with (All: All samples, S1: Study1 samples, S2: Study2 samples, M: Male samples, F: Female samples, C: Cortical features, S: Subcortical features). The numbers in the table are accuracies (ratio of correct predictions (positive or negative)

	All→C	All→S	S1→C	S1→S	S2→C	S2→S	M→C	M→S	F→C	F→S
Physical 1	0.65	0.60	0.65	0.60	0.58	0.66	0.55	0.55	0.62	0.61
Physical 2	0.77	0.76	0.83	0.82	0.73	0.71	0.68	0.72	0.83	0.82
Physical 3	0.84	0.86	0.82	0.85	0.86	0.86	0.92	0.94	0.79	0.80

Table 5.21: Classifying Physical Abuse using Random Forest Method. The number in front of word "Physical" denotes the severity of this abuse type, 1 being the least and 3 being the most severe. We choose the initial subset of samples and features that we start our training with (All: All samples, S1: Study1 samples, S2: Study2 samples, M: Male samples, F: Female samples, C: Cortical features, S: Subcortical features). The numbers in the table are accuracies (ratio of correct predictions (positive or negative)

	All→C	All→S	S1→C	S1→S	S2→C	S2→S	M→C	M→S	F→C	F→S
Sexual 1	0.81	0.79	0.82	0.82	0.80	0.80	0.87	0.87	0.76	0.76
Sexual 2	0.89	0.89	0.92	0.92	0.88	0.88	0.94	0.94	0.85	0.85
Sexual 3	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.91	0.91

Table 5.22: Classifying Sexual Abuse using LASSO Method. The number in front of word "Sexual" denotes the severity of this abuse type, 1 being the least and 3 being the most severe. We choose the initial subset of samples and features that we start our training with (All: All samples, S1: Study1 samples, S2: Study2 samples, M: Male samples, F: Female samples, C: Cortical features, S: Subcortical features). The numbers in the table are accuracies (ratio of correct predictions (positive or negative)

	All→C	All→S	S1→C	S1→S	S2→C	S2→S	M→C	M→S	F→C	F→S
Sexual 1	0.82	0.81	0.78	0.82	0.78	0.80	0.85	0.87	0.76	0.76
Sexual 2	0.89	0.89	0.90	0.90	0.88	0.88	0.94	0.94	0.85	0.85
Sexual 3	0.87	0.87	0.90	0.90	0.85	0.85	0.91	0.91	0.85	0.85

Table 5.23: Classifying Sexual Abuse using Random Forest Method. The number in front of word "Sexual" denotes the severity of this abuse type, 1 being the least and 3 being the most severe. We choose the initial subset of samples and features that we start our training with (All: All samples, S1: Study1 samples, S2: Study2 samples, M: Male samples, F: Female samples, C: Cortical features, S: Subcortical features). The numbers in the table are accuracies (ratio of correct predictions (positive or negative)

5.2.4 Other Features

Finally, I classified extra features that are available in the dataset. These features are:

- Marital Status of Parents
- IQ: If IQ of the sample is more than 100 or not
- Number of Parents with income (0 to 2)
- Education Level of Parents: divided the samples into 4 categories based on parents education level, 1 having at most High School education and 4 having a graduate degree.

The columns are similar to previous subsection. I try both LASSO and Random Forest here as well.

	All→C	All→S	S1→C	S1→S	S2→C	S2→S	M→C	M→S	F→C	F→S
Education 1	0.76	0.76	0.78	0.70	0.84	0.84	0.73	0.69	0.79	0.74
Education 2	0.85	0.85	0.91	0.91	0.78	0.78	0.87	0.87	0.83	0.83
Education 3	0.77	0.77	0.76	0.76	0.78	0.78	0.75	0.75	0.79	0.79
Education 4	0.60	0.62	0.65	0.65	0.55	0.61	0.62	0.65	0.57	0.58
Income 0	0.77	0.76	NA	NA	0.63	0.66	0.16	0.16	0.25	0.25
Income 1	0.59	0.58	0.53	0.53	0.66	0.64	0.61	0.61	0.54	0.60
Income 2	0.56	0.56	0.47	0.51	0.71	0.71	0.35	0.55	0.63	0.56
Marital Stat	0.57	0.54	0.59	0.59	0.57	0.36	0.49	0.40	0.63	0.44
IQ	0.62	0.40	0.68	0.65	0.51	0.55	0.55	0.57	0.53	0.57

Table 5.24: Classifying Various Features using LASSO Method. The rows in the table denote different classes we try to classify. Education is mentioned in 4 categories. Education 1 is No education at all. Education 2 is highschool education. Education 3 is college degree and Education 4 is graduate degree. The number in front of "Income" is the number of people within the household with an income. Marital Stat denotes the marital status of parents (married or divorced) and IQ represents the binary class of children with IQ greater than 100 and under 100. We choose the initial subset of samples and features that we start our training with (All: All samples, S1: Study1 samples, S2: Study2 samples, M: Male samples, F: Female samples, C: Cortical features, S: Subcortical features). The numbers in the table are accuracies (ratio of correct predictions (positive or negative)

	All→C	All→C	S1→C	S1→S	S2→C	S2→S	M→C	M→C	F→C	F→S
Education 1	0.74	0.76	0.81	0.80	0.84	0.84	0.71	0.71	0.79	0.79
Education 2	0.85	0.83	0.91	0.91	0.78	0.78	0.85	0.85	0.83	0.83
Education 3	0.76	0.72	0.70	0.72	0.78	0.76	0.73	0.71	0.79	0.79
Education 4	0.56	0.60	0.59	0.56	0.61	0.69	0.62	0.69	0.49	0.55
Income 0	0.78	0.79	NA	NA	0.59	0.63	0.16	0.82	0.74	0.75
Income 1	0.55	0.55	0.55	0.43	0.66	0.68	0.59	0.55	0.61	0.51
Income 2	0.62	0.56	0.60	0.45	0.69	0.66	0.49	0.49	0.63	0.61
Marital Stat	0.49	0.52	0.58	0.59	0.42	0.47	0.47	0.42	0.41	0.46
IQ	0.58	0.61	0.68	0.65	0.45	0.38	0.62	0.53	0.50	0.50

Table 5.25: Classifying Various Features using Random Forest Method. The rows in the table denote different classes we try to classify. Education is mentioned in 4 categories. Education 1 is No education at all. Education 2 is highschool education. Education 3 is college degree and Education 4 is graduate degree. The number in front of "Income" is the number of people within the household with an income. Marital Stat denotes the marital status of parents (married or divorced) and IQ represents the binary class of children with IQ greater than 100 and under 100. We choose the initial subset of samples and features that we start our training with (All: All samples, S1: Study1 samples, S2: Study2 samples, M: Male samples, F: Female samples, C: Cortical features, S: Subcortical features). The numbers in the table are accuracies (ratio of correct predictions (positive or negative)

5.3 Feature Selection

With only about 100 samples, I was given more than 500 features. These features include subcortical volumes and cortical thickness, area and volumes. For classification of child maltreatment, I considered each of these categories independently to see if fewer features would enhance the features selected by our classification methods.

This section only focuses on feature selection for child maltreatment classification. Since LASSO and Random Forest gave us the best accuracies for child maltreatment prediction (details in Section 5.4), I focused on features that emerge from these methods. More importantly, papers about machine learning on brain imaging data [40, 2], advocate linear models as the best methods for classification and regression for MRI data. Based on these facts, I focused on features chosen by LASSO which is a method which is based on linear models. This means that the larger the coefficients of features in linear formula that comes out of LASSO, the more important that feature is in predicting the class.

Our results indicated that thickness of cortical regions were the main features driving the LASSO method. Indeed, some yet unpublished papers also point in this direction that child maltreatment is most visible in thickness data rather than volume or area in cortical regions. The share of subcortical regions are also insignificant with respect to thickness of cortical regions.

Based on literature, Of all cortical regions, six regions are the main ones altered by childhood maltreatment [28, 29, 1]:

1. Medial OFC (Obitofrontal Cortex)

2. Parahippocampal gyrus

3. Superior temporal gyrus

4. Middle temporal gyrus

5. Inferior temporal gyrus

6. Inferior frontal gyrus

Our LASSO method found eight major thickness features in the following order:

- Occipital middle thickness

- Temportal medial and Lingual thickness (Part of Middle temporal gyrus)
- Temportal Transverse thickness
- Rectus thickness (Part of Medial OFC)
- Temporal lateral Fusifor thickness
- Temporal medial Parahippocampal thickness (Part of Parahippocampal gyrus)
- Subcentral thickness
- Middle and Lunatus thickness

I showed that three out of eight features found were also mentioned in the literature as indicator of child maltreatment.

5.4 Discussion

In this section, I discuss and explain all the results from previous sections and compare our results with the ones available in the related works.

5.4.1 Classifying Child Maltreatment

In Section 5.1, I observed many results in the form of accuracies in tables. I will draw observations out of them below:

- Of all eight classification methods, LASSO and Random Forest came up with the best accuracies. LASSO did slightly better than Random Forest in classifying child maltreatment. That was the reason why I only used them in classifying other features in Section 5.2.

- Training the data by one study and testing the model by the other study gave poor results. The same issue occurred with training and testing with different genders. This led us to only use cross validation in Section 5.2.

- Considering all features or a part of them do not have a major impact in the accuracy of the results. However, by only considering subcortical regions, I manage to get slightly higher accuracies. This will prove to be not indicating much later though, because cortical thickness differences between maltreated group and control group is the main indicator of child maltreatment.

5.4.2 Classifying Other Features

With trying to classify various features other than child maltreatment, came very interesting observations. I talk about them here:

- LASSO and Random Forest were the only methods considered in Section 5.2. The results indicate that they come up with very similar accuracy results. However, based on the results, LASSO is doing slightly better.

- Accuracies for classifying gender are very good. This was predictable though based on many publications on differences in brain structure between males and females [18].

- In age prediction, I get much better results predicting children under 14 than predicting other groups. In other words, I can predict children vs. adolescents than predicting adolescents over 17 vs. under 17.

- In predicting abuse types, I divided each abuse type into 3 degrees based on their severity. I can predict most severe case (degree 3) of emotional abuse better than other other two degrees. I can also predict physical abuses of degrees 2 and 3 very well. As for sexual abuse, I predict all 3 degrees of them very efficiently. I can consider emotional, physical and sexual abuse themselves to be in order in terms of severity of general abuse. All of these suggest that, as severity of abuse toward the child increases I can predict them better. I consider this fact as one of our most important results throughout this thesis.

- Results for prediction of IQ of children, marital status and income levels in the family of children are very close to random decision (50 percent) and thus not achievable through this dataset, at least with the methods I tried.

- Education levels of parents can be predicted based on brain structure of children only when considering parents with no education or high school education versus parent with college education and higher. When comparing parents with higher degrees such as graduate degrees with other parents, I have not been able to classify that efficiently.

5.4.3 Feature Selection

I found 8 features of importance when applying LASSO to our dataset for classifying child maltreatment in Section 5.3. I showed that 3 of those features are supported by the literature and 5 are new features found by us. I consider this another major result of this research.

Chapter 6
CONCLUSION

In this chapter, I summarize our thesis and also give directions for future works on this subject.

6.1 Summary

Classification and prediction of child maltreatment by brain imaging data is a well-known and well-studied field. This thesis also works toward providing more results in this subject using machine learning as its main technique.

I started this thesis in Chapter 1 with motivation of this project, introduction to clinical psychology and neuroimaging. In Chapter 2, I introduced machine learning and explained how I can make use of it to predict features in a dataset. In Chapter 3, I introduced the brain imaging dataset in detail. Chapters 4 and 5, are the results chapters. In chapter 4, I present visualization results on classifying child maltreatment, gender and age. Finally in chapter 5, I present the classification method and feature selection results on classifying child maltreatment, gender, age, abuse types and other classes.

6.2 Directions for Future Work

This project can be extended in many aspects and dimensions. I mention some of them here:

- With this dataset: Obviously, I cannot claim that I have completely finished this project and considered all possible options. Conversely, I tried to assess many different possible options for classification method, feature selection, choosing sub-samples and choosing features other than child maltreatment. Any of these dimensions can be worked on and extended.

- With PING dataset: PING Study [55], which stands for Pediatric Imaging, Neurocognition, and Genetics, is a study on more than 1000 children with their brain imaging data and genetic data. Although, child maltreatment is not assessed in this data, many other classes such as ADHD (Attention-deficit-hyperactivity-disorder) are considerable as classes to predict and classify.

- With another dataset: This research couldn't be done without working directly with Stress and Development Lab who provided us with the dataset and aspects of this project. Definitely, many other Labs around the country have data on child maltreatment that can be accessed and worked on.

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