# Machine Learning on Brain Graph

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### Introduction

- fMRI: functional magnetic resonance imaging that reveals the activity of brain region based on blood flow [1]
- Brain graph: graphical representation of brain that shows the connectivity among regions
  - Region of brain: node
  - Connection/correlation between regions: edges
- Together: diagnosis of brain diseases [2]

### **Project Goal**

The goal of this project is to develop a machine learning solution that can

- take fMRI data from public sources as input
- distinguish fMRI samples with ASD (Autism) Spectrum Disorder) from healthy control

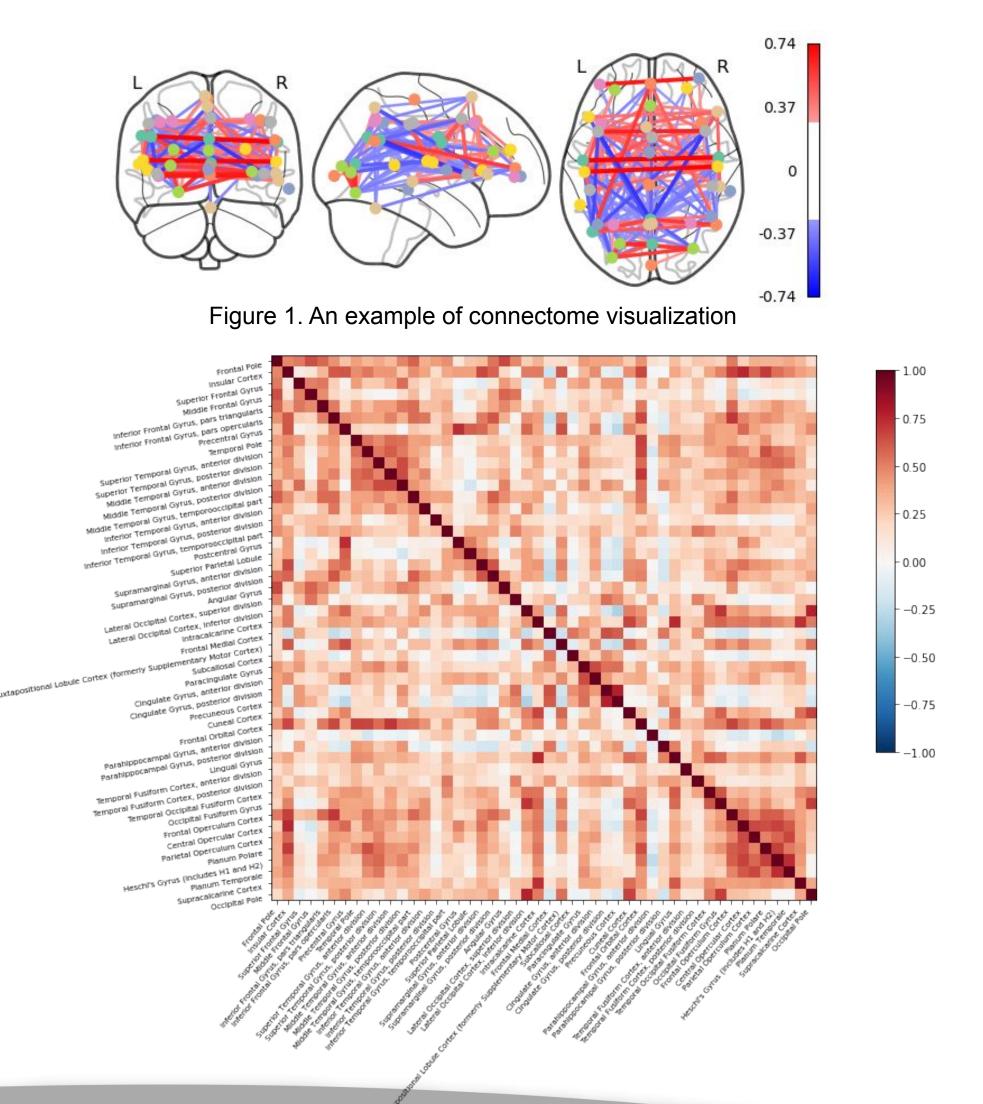


Figure 2. An example of connectivity matrix (brain graph) visualization

### Final Design

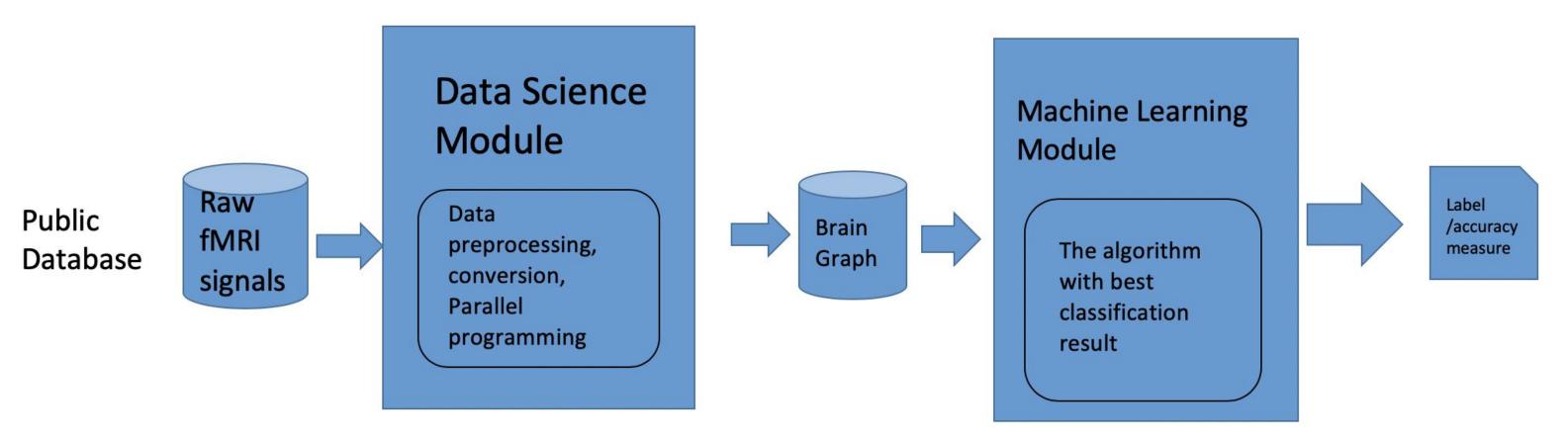


Figure 3. System block diagram

#### **Data Science module:**

Files (matrix.csv

collects and labels resting state fMRI from preprocessed ABIDE (Autism Brain Imaging Data Exchange) database, converts to brain graphs and stores as csv files [3] Highlights:

- brain regions: the mask used for correlation calculation is the 48 cortical regions defined by the Harvard-Oxford parcellations [4]
- sample size: healthy control: 468, ASD patient: 403

Each

selected

The model

Figure 4. Detailed block diagram for the machine learning module

#### **Machine Learning module:**

Separates the incoming dataset into a training set and a validation set. Then, trains a machine learning model for every selected algorithm, based on the training set. Lastly, evaluates and selects the best model (Figure 4). Highlights:

The algorithms implemented are shown in Table 1

Table 1. The chosen classification model and the corresponding description for the machine learning module

| Model   | Description  |  |  |
|---|--|--|--|
| Support Vector<br>Machine (SVM)                             | A traditional algorithm proven strong as a classifier.   |  |  |
| SVM with<br>Gaussian kernel<br>(RBF SVM)                    | Improvement on SVM with a radial basis function kernel usually resulting in smoother functions, thus improving classification.   |  |  |
| multi-layer<br>perceptron (MLP)                             | The basic version of neural network, which is proven to be very effective to do classification.  |  |  |
| Convolutional<br>Neural Network<br>(CNN)                    | Typically used to classify images and an adjacency matrix can be viewed as a mono-channel image  |  |  |
| DeepWalk + MLP<br>[5]                                       | Both DeepWalk and SDNE are graph embedded algorithm. Firstly, compute a vector representation for each vertex of a graph. Then, these vectors are fed into MLP model do the classification work. |  |  |
| Structural Deep<br>Network<br>Embedding<br>(SDNE) + MLP [6] |  |  |  |

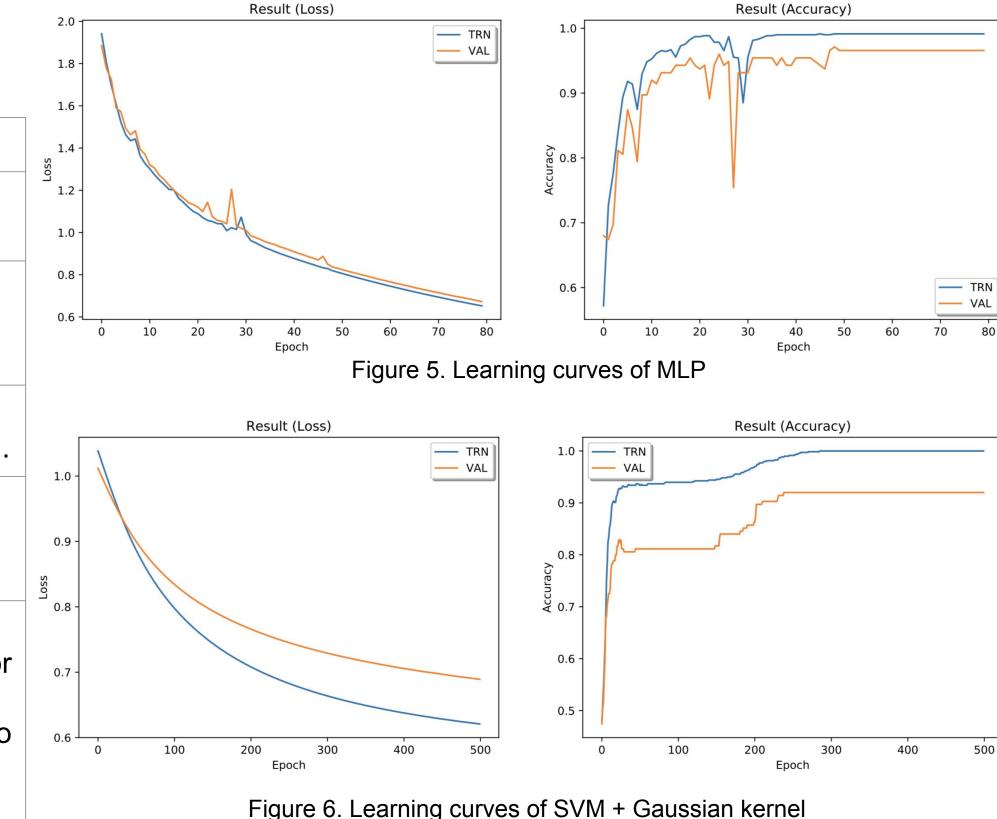
## **Result and Conclusion**

Based on the accuracy shown in Table 2, we chose the model based on MLP algorithm as the optimal model.

- this is expected as MLP is proven to be effective for classification. However we did expect DeepWalk and SDNE will improve the accuracy and this was the case when testing with synthetic data. But in reality, the brain graph can be noisier and more complex than the synthetic data.

Table 2. Performance of each model

| Algorithm         | Training<br>Loss | Training Accuracy | Validation<br>Loss | Validation<br>Accuracy |
|-------------------|------------------|-------------------|--------------------|------------------------|
| basic SVM         | 0.592192         | 97%               | 0.626772           | 92%                    |
| RBF SVM           | 0.620976         | 100%              | 0.689268           | 92%                    |
| MLP               | 0.656901         | 99%               | 0.677377           | 97%                    |
| CNN               | 0.69032          | 54%               | 0.693904           | 51%                    |
| DeepWalk +<br>MLP | 0.346648         | 99%               | 0.797786           | 50%                    |
| SDNE + MLP        | 0.394087         | 99%               | 0.878836           | 49%                    |



<sup>[1]</sup> J. Richiardi, H. Eryilmaz, S. Schwartz, P. Vuilleumier and D. V. De Ville, "Decoding brain states from fMRI connectivity graphs," *Neuroimage*, May-2011. [Online]. Available:

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https://ieeexplore.ieee.org/document/7738852. [Accessed: 1-Oct-2018]. [3] 1000 Functional Connectomes Project, "Autism Brain Imaging Data Exchange". [Online]. Available: http://fcon 1000.projects.nitrc.org/indi/abide/. [Accessed: 7-Jan-2019] [4]Nikos Makris, Jill M. Goldstein, David Kennedy, Steven M. Hodge, Verne S. Caviness, Stephen V. Faraone, Ming T. Tsuang, Larry J. Seidman (2006). "Decreased volume of left and total anterior insular lobule in schizophrenia". Schizophrenia research 83(2-3): 155-151. doi: 10.1016/j.schres.2005.11.020. PMID: 16448806.

<sup>[5]</sup> B. Perozzi, R. Al-Rfou, S. Skiena. "DeepWalk: Online Learning of Social Representations". Stony Brook University, 27-Jun-2014. [Online]. Available: https://arxiv.org/pdf/1403.6652.pdf. [Accessed: 17-Mar-2019] [6] Daixin Wang, Peng Cui, Wenwu Zhu. "Structural Deep Network Embedding". Tsinghua University, Aug-2016. [Online]. Available: https://www.kdd.org/kdd2016/papers/files/rfp0191-wangAemb.pdf. [Accessed: 17-Mar-2019]