

## Prediction of Age and Biological Sex using Spatial-Temporal Graph CNN on fMRI Scans

Soham Gadgil, Sun Woo Kang, Erick Fidel Siavichay-Velasco {sgadgil, swkang73, esiavich}@stanford.edu

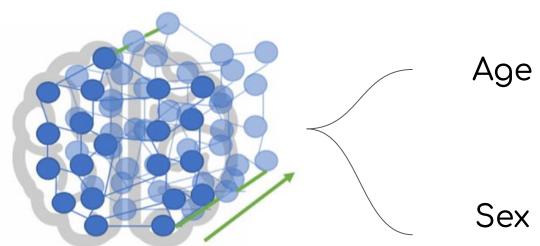
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### Introduction

- The Human Connectome Project aims to build a complete functional and structural map of the human brain
- We use their fMRI and structural MRI brain scans to predict sex and age
- We use a novel approach by employing ST-GCN
- This research project can be used to discover and improve understanding of sex-linked and age-related neurological diseases

### Problem

- Given a 4D brain scan, classify age and sex of a patient
- Regression on age, binary classification of age (old, young adult) and sex (male, female)



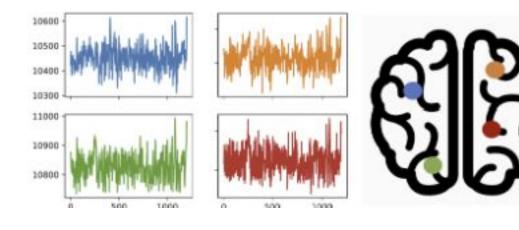
4D Brain Scan

- ST-GCN Test Accuracies
  - Age: 63%, Sex: 78%

### Dataset

- Original input data
  - fMRI scans from 1108 healthy individuals, 603 female, 505 male
  - Each file is of 200 brain regions of 1,200 timesteps
- Data augmentation
  - Each file was fragmented into 100 time steps, which resulted in 12 fragments
  - Coarser brain sampling (22 brain regions instead of 200)
  - This resulted in 13,082 samples

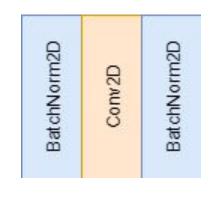
### Feature Mapping



- Brain regions act as nodes in the graph. Correlation between regions act as edges
- Adjacency matrix captures correlations of brain region across timesteps
- Feature mapping is computed by using

$$f_{out} = D^{-1/2}(A+I)D^{-1/2}f_{in}W$$

### ST-GCN Unit and Model



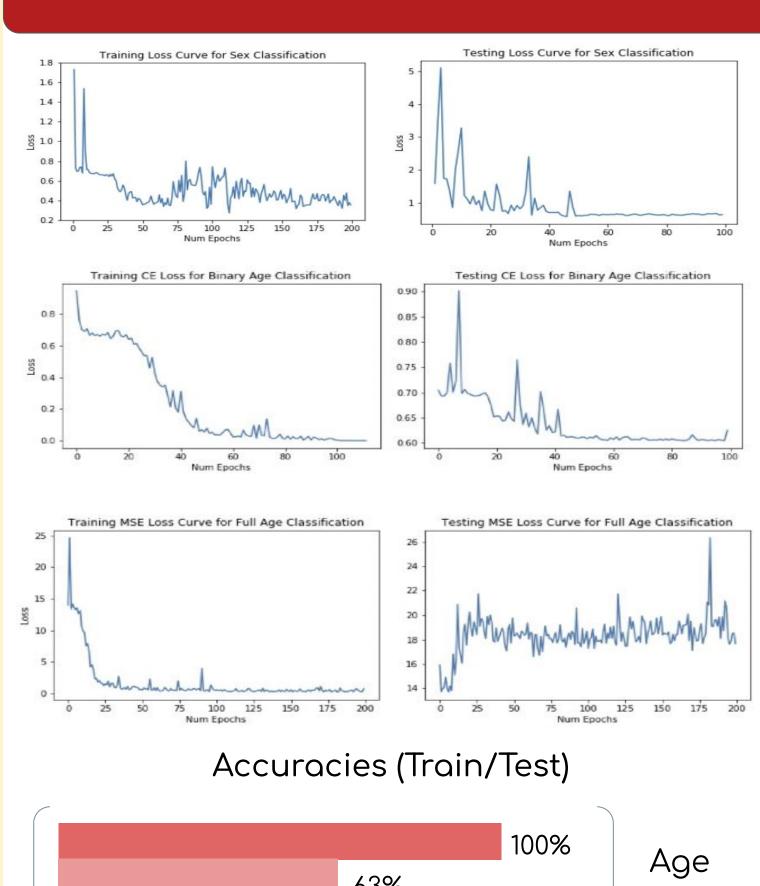
- ST-GCN UnitReLU Activation
- No dropout

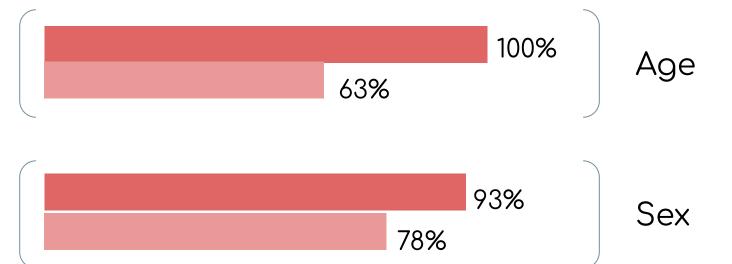
# BatchNorm ST-GCN Units (64 output channels) ST-GCN Units (128 output channels) ST-GCN Units (256 output channels)

 Final layer predictions computed with and without Softmax for binary and real-number outputs

$$\mathcal{L}(y_i, \hat{y_i}) = -\frac{1}{m} \sum_{i=1}^m y_i log(\hat{y_i}) + (1 - y_i) log(1 - \hat{y_i})$$
 CE Loss 
$$\mathcal{L}(y_i, \hat{y_i}) = \frac{1}{m} \sum_{i=1}^m (y_i - \hat{y_i})^2$$
 MSE Loss

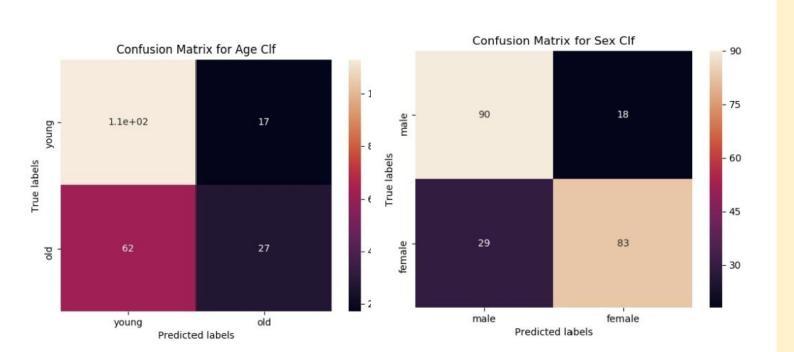
### Results





### Discussion

	Precision	Recall	F1 Score
Age	0.6457	0.8692	0.741
Sex	0.7563	0.833	0.793



- Model show similar accuracies for male and female brains but predicted male more often
- Age classification accuracy lower, but model was still able to distinguish age bins

#### **Future Work**

- Large gap in train/test accuracies suggest we use dropout and weight regularization
- Analyze subject level prediction instead of sample level prediction for better accuracies

### Notable References

For full list please checkout github.com/ericksiavichay/cs230-final-project

- . Kipf, T.N., Welling, M.: Semi-Supervised Classification with Graph
- Convolutional Network <a href="https://arxiv.org/abs/1609.02907">https://arxiv.org/abs/1609.02907</a>
  2. Li, X., et al: Graph Neural Network for Interpreting Task-fMRI
- Biomarkers https://arxiv.org/abs/1907.01661
  3. Yan, S., Xiong, Y., Lin, D.: Spatial Temporal Graph Convolutional Networks (ST-GCN) for Skeleton-Based Action Recognition in PyTorch https://github.com/yysijie/st-gcn